Predictive Seam-Tracking Optimization

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Abstract

In this paper an algorithm for sensor guided manipulators is presented, where sensor information, manipulator dynamics and a path generator model are combined to minimize the tracking error. Feedback linearization-decoupling permits the use of linear SISO prediction models for the dynamics of each robot joint. Scene interpretation of CCD-camera images generates spline fitted segments of future trajectory. In the sensor vision field the proposed optimization criteria minimizes the error between state variables of the prediction model and the state variables of the spline trajectory generator. These technique, allied with separation of disturbance rejection and path-tracking performance by the proposed feed-forward ***Following Model Predictive (FMP)*** *servo-controller design, permits very high path tracking dynamics (and consequently small errors). Experimental results on implementation of a CCD-camera guided hydraulic robot demonstrates the practical relevance of the proposed approach for welding robots.*

Introduction

Robotic manipulators have been used in welding cells for long time in order to improve welding quality. Substitution of mancraft in welding cells where a robot welds only few different parts every time in the same manner, such as in spot welding commonly used in the automobile industry, is not a very difficult task. But in a flexible, just-in-time, and CAD customized production approach, very different parts are to be welded demanding an "*intelligent*" robot-welding concept.

Providing robots with abilities of an experienced welder is the visionary target of many research groups. The realization of such ambitious goal leads to the use of sensors, which provide the robot with the necessary information, so that it can interact within their environment. Preferentially, the robot should autonomously find and precisely weld metal joining paths in order to fulfill some given manufacturing task [1].

A shortcut of the use of sensor-guided robots is that due to their mechanical inertia they can react only relatively slowly to changes in the trajectory information captured by the sensor system. In this paper it will be shown how a sensor that can look ahead, such as a CCD-camera, can be used to improve substantially the seam tracking precision. The proposed algorithm virtually eliminates the tracking error by considering the dynamic model of the robot and the captured future trajectory information. Incorporating an internal trajectory generator model leads thus to the ***F****ollowing* ***M****odel* ***P****redictive* servo-controller algorithm (***FMP*** **-** for short [3]).

Non-linear control techniques [4],[5] can decouple and linearize robotic manipulator joints. So that each robot joint can be considered as a linear SISO system. Using such model, the tracking problem of sensor guided manipulators can be treated in the linear domain. In particular, the discrete optimization of the predictive path-tracking problem with the proposed cost function leads to an analytical solution with guaranteed stability [3],[8]. This new approach avoids the typical recursive solution usually employed for the Riccati equation [2].

Robotic manipulators equipped with sensors can automate industrial processes in an "intelligent manner". Those are objects of intense research efforts in the field of Artificial Intelligence (AI): to build machines that consider the information captured from the surrounding environment in a proper (intelligent) manner. With the support of sensors the working trajectory of the robot can be obtained within a certain vision field, which will be used here as the minimization horizon of the tracking error.

The proposed algorithm was implemented to control a hydraulic manipulator guided by a CCD-camera, where it was showed that the ***FMP*** methodology significantly reduces the dynamic tracking error. Currently this technique is being implemented to control a 6-DOF CCD-camera guided welding robot at GRACO.

Dynamic system tracking

Depending on the characteristics of tracking the following classification of problems are usual, [2]:

- The tracking problem:

The reference trajectory is a determined (arbitrary) function of time for 0 < t < T.

- The servo problem:
  The system is to be controlled in such a manner that the controlled variable will follow a reference signal from which it is only known that it belongs to a certain signal class, e.g. a sequence of steps or polynoms until a certain order.
- The model following problem:
  The output of the servo-system should follow the output of a path generator.

For sensor-guided robotic manipulators the tracking problem is to be solved, because the captured trajectory is not known a priori. For the model following problem it is possible to obtain *ideal following*, i.e. zero tracking error in every time instant [10]. A proper path generator for robotic manipulators is an integrator chain, which in the case of three chained integrators produce *spline* polynoms.

Despite ideal following can not be obtained for sensor guided manipulators, their basic idea will be used here: minimize the error between the state variables of the controlled system and the state variables of a path generator internal model.

Following Model Predictive path tracking

Consider the controllable and observable scalar n-th order discrete time linear system described by:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}_k\mathbf{x}(k) + \mathbf{b}_k u_s(k); \qquad \mathbf{x}(0) = \mathbf{x}_0 \\ y(k) &= \mathbf{c}_k^T\mathbf{x}(k), \end{aligned} \tag{1}$$

where $\mathbf{x}(k)$ is the nx1 state vector at time $t=kT$ (T is the sampling period), $u_s(k)$ is the input and $y(k)$ is the system output.

This model, with n=3, will be used here for robotic manipulators that are linearized and decoupled by an underlying non-linear multivariable joint controller. The resulting integrator chain that is obtained, for example by the inverse system controller [4],[5] is then transformed in a P-T_n system by means of linear state feedback. Finally the discrete model, Eq. 1, is obtained using a Step Invariant Transformation [10]. That model will be here, therefore, denominated ***predictor model***, because it allows the prediction of the dynamic behavior of each robot joint for a given reference trajectory.

Problem formulation

Given an n-th order plant described by Eq. 1. The reference trajectory and its derivatives $w(t)$, $\dot{w}(t),\ldots w^{(n-1)}(t)$ are known from $t = (k+1)T$ until the horizon $t = (k+m)T$. The current state of the plant is $\mathbf{x}(k)$. The position, velocity, acceleration, and higher derivatives of the controlled variable correspond to the states of the system in the controllable canonical form. The problem consists on the calculation of the control sequence $u_s(k)$, $u_s(k+1)$, ... $u_s(k+m-1)$, such that the following *predictive path tracking* ***Optimization Criteria*** (or ***Cost Function***) will be minimized:

$$J = \sum_{i=0}^{n-1} \varepsilon_i^T \mathbf{Q}_i \varepsilon_i + \beta^T \mathbf{R} \beta \tag{2}$$

The weighting matrices $\mathbf{Q}_i$ and $\mathbf{R}$ are symmetric positive defined. In the most general case these matrices can be time dependent. The vector error terms ε_i are:

Position Error: $\varepsilon_0(k) \hat{=} \mathbf{y}(k) - \mathbf{w}(k)$ (3)

$$\mathbf{y}(k) \hat{=} \begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+m) \end{bmatrix}, \mathbf{w}(k) \hat{=} \begin{bmatrix} w(k+1) \\ w(k+2) \\ \vdots \\ w(k+m) \end{bmatrix},$$

Velocity Error: $\varepsilon_1(k) \hat{=} \dot{\mathbf{y}}(k) - \dot{\mathbf{w}}(k)$ (4)

$$\dot{\mathbf{y}}(k) \hat{=} \begin{bmatrix} \dot{\hat{y}}(k+1) \\ \dot{\hat{y}}(k+2) \\ \vdots \\ \dot{\hat{y}}(k+m) \end{bmatrix}, \dot{\mathbf{w}}(k) \hat{=} \begin{bmatrix} \dot{w}(k+1) \\ \dot{w}(k+2) \\ \vdots \\ \dot{w}(k+m) \end{bmatrix}, \ldots$$

Error in the n-1 derivative:

$\varepsilon_{n-1}(k) \hat{=} \mathbf{y}^{(n-1)}(k) - \mathbf{w}^{(n-1)}(k)$ (5)

$$\mathbf{y}^{(n-1)}(k) \hat{=} \begin{bmatrix} \hat{y}^{(n-1)}(k+1) \\ \hat{y}^{(n-1)}(k+2) \\ \vdots \\ \hat{y}^{(n-1)}(k+m) \end{bmatrix}, \mathbf{w}^{(n-1)}(k) \hat{=} \begin{bmatrix} w^{(n-1)}(k+1) \\ w^{(n-1)}(k+2) \\ \vdots \\ w^{(n-1)}(k+m) \end{bmatrix},$$

Energy: $\beta(k) \hat{=} \mathbf{u}_s(k) - \mathbf{w}(k)$ (6)

$$\mathbf{u}_s(k) \hat{=} \begin{bmatrix} u_s(k) \\ u_s(k+1) \\ \vdots \\ u_s(k+m-1) \end{bmatrix}.$$

The searched control sequence is also described by the vector $\mathbf{u}_s$ (k). Each vector error term in Eq. 2 embraces a prediction horizon of m samples. The design matrices $\mathbf{Q}_i$ and $\mathbf{R}$ weight the corresponding error terms leading to a scalar cost function J. For diagonal $\mathbf{Q}_i$ and $\mathbf{R}$ the cost function J reduces to a weighted sum of quadratic errors that penalizes reference deviations in each state space variable (i.e., position, velocity, acceleration, and so on) over the known m future sampling times. As will be shown later, choice of the elements in $\mathbf{Q}_i$ and $\mathbf{R}$ (this is thus the design procedure) establishes a particular dynamic behavior of a ***FMP*** servo-controlled system.

The last vector term $\beta(k)$, the control variable displacement, stands in the cost function for energy limitation. It constrains the control signal $u_s(k)$ in the vicinity of the actual set point $w(k)$. It can be assumed, without loss of generality, that the gain of the linearized scalar system Eq. 1 is unitary (in steady state $u_s(k) = w(k)$). In the literature [9], control signal limitation is also considered using $\beta'(k) \triangleq \mathbf{u}_s(k)$ for plants with integrating characteristic and by $\beta''(k) \triangleq \mathbf{u}_s(k+1) - \mathbf{u}_s(k)$ otherwise.

The proposed ***predictive path tracking Optimization Criteria***, Eq. 2**,** not only minimizes the average deviation between controlled variable $y(k)$ and reference signal $w(k)$ considering energy limitation, as usual in most predictive algorithms [6],[9], but generalizes, considering ***all information*** available: 1) the state space variables of the controlled system, 2) the future trajectory captured in the sensor vision field, and 3) the state space variables of a trajectory generator model.

The proposed use of "all information" can even supply a great lack in the predictive control theory: guaranteed closed loop stability [3],[8]. Indeed [8] shows the equivalence of the proposed ***FMP*** algorithm to a discrete version of the Riccati LQ-controller, which as observed by Kalman [2] is closed loop stable.

Calculation of the optimal control sequence

Beginning with the state-space description Eq. 1,

$$y(k) = \begin{bmatrix}1 & 0 & \cdots & 0\end{bmatrix}\mathbf{x}(k) = \mathbf{c}_0^T\mathbf{x}(k),$$

$$\dot{y}(k) = \begin{bmatrix}0 & 1 & \cdots & 0\end{bmatrix}\mathbf{x}(k) = \mathbf{c}_1^T\mathbf{x}(k),$$

$$\cdots$$

$$y^{(n-1)}(k) = \begin{bmatrix}0 & 0 & \cdots & 1\end{bmatrix}\mathbf{x}(k) = \mathbf{c}_{n-1}^T\mathbf{x}(k),$$

it is possible to predict the system "output" vectors $\mathbf{y}, \dot{\mathbf{y}}, \ldots \mathbf{y}^{(n-1)}$ comprising the time points $t=k+1$ up to $t=k+m$. The following relations can be given:

$$\mathbf{y}(k) = \mathbf{G}_0\mathbf{x}(k) + \mathbf{H}_0\mathbf{u}_s(k), \qquad (7)$$

$$\dot{\mathbf{y}}(k) = \mathbf{G}_1\mathbf{x}(k) + \mathbf{H}_1\mathbf{u}_s(k),$$

$$\cdots$$

$$\mathbf{y}^{(n-1)}(k) = \mathbf{G}_{n-1}\mathbf{x}(k) + \mathbf{H}_{n-1}\mathbf{u}_s(k).$$

The matrices $\mathbf{G}_\mu$, $\mathbf{H}_\mu$, with μ= 0,1,... n-1, are given by

$$\mathbf{G}_\mu = \begin{bmatrix}\mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A} \\ \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A}^2 \\ \vdots \\ \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A}^m\end{bmatrix}, \quad \mathbf{H}_\mu = \begin{bmatrix}\mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{b} & 0 & \cdots & 0 \\ \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A}\mathbf{b} & \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{b} & & 0 \\ \vdots & & \ddots & \vdots \\ \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A}^{m-1}\mathbf{b} & \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{A}^{m-2}\mathbf{b} & \cdots & \mathbf{c}_\mu{}^{\mathbf{T}}\mathbf{b}\end{bmatrix}.$$

Using Eqs. 3 to 6 we express the criterion J as a function of $\mathbf{w}(k), \dot{\mathbf{w}}(k), \ldots \ \mathbf{w}^{(n-1)}(k)$, $\mathbf{x}(k)$ and $\mathbf{u}_s(k)$:

$$J = \sum_{i=0}^{n-1}[\mathbf{G}_i\mathbf{x}(k) + \mathbf{H}_i\mathbf{u}_s(k) - \mathbf{w}^{(i)}(k)]^T \cdot\mathbf{Q}_i[\mathbf{G}_i\mathbf{x}(k) + \mathbf{H}_i\mathbf{u}_s(k) - \mathbf{w}^{(i)}(k)] + [\mathbf{u}_s(k) - \mathbf{w}(k)]^T\mathbf{R}[\mathbf{u}_s(k) - \mathbf{w}(k)].$$

This equation has, with exception of the searched control sequence, only known variables. So, from that equation we can calculate the searched control sequence $\mathbf{u}_s(k)$ by setting the vector of the partial derivatives $\partial J / \partial \mathbf{u}_s(k)$ to zero to obtain:

$$\left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{H}_i + \mathbf{R}\right]\mathbf{u}_s(k) + \left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{G}_i\right]\mathbf{x}(k) - \left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{w}^{(i)}(k) + \mathbf{R}\mathbf{w}(k)\right] = \mathbf{0},$$

from which we obtain the following result:

$$\mathbf{u}_s(k) = \left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{H}_i + \mathbf{R}\right]^{-1} \cdot\left\{\left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{w}^{(i)}(k) + \mathbf{R}\mathbf{w}(k)\right] - \left[\sum_{i=0}^{n-1}\mathbf{H}_i{}^T\mathbf{Q}_i\mathbf{G}_i\right]\mathbf{x}(k)\right\}. \qquad (8)$$

With exception of the not allowed case $\mathbf{Q}_i$=$\mathbf{R}$=$\mathbf{0}$**,** the inverse matrix exists.

To apply this algorithm to robotic manipulators it will be assumed that an underlying nonlinear joint control scheme is being used, which decouple and linearize each robot joint. The dynamic of each joint will be considered as P-T_3. Consequently the ***FMP*** servocontroller will be designed for such SISO systems.

The control sequence, Eq. 8, can be interpreted as a linear, periodic (with period $m \cdot T_s$) *time-variant* pre-filtering of the reference vectors $w(k)$, $\dot{w}(k)$ and $\ddot{w}(k)$ with a linear state feedback also *time-variant*. This can be better recognized in the following reformulation of Eq. 8 for a 3rd order system:

$$\mathbf{u}_s(k) = \mathbf{M}_w\mathbf{w}(k) + \mathbf{M}_{\dot{w}}\dot{\mathbf{w}}(k) + \mathbf{M}_{\ddot{w}}\ddot{\mathbf{w}}(k) - \mathbf{M}_x\mathbf{x}(k), \qquad (9)$$

where $\mathbf{M}_w, \mathbf{M}_{\dot{w}}$ and $\mathbf{M}_{\ddot{w}}$ are matrices of order m x m, and $\mathbf{M}_x$ is m x 3. Observing each line of this vector equation it can be seen that the control signal $u_s(k+\nu)$, i.e. the signal in the time point ν in the minimizing horizon $k...k+m-1$, is dependent on system state in the starting instant of the minimization $\mathbf{x}(k)$ and from all reference trajectory values

$w(k), \dot{w}(k)$ and $\ddot{w}(k)$ in that minimization horizon ($\mathbf{w}(k), \dot{\mathbf{w}}(k)$ and $\ddot{\mathbf{w}}(k)$).

The computation of the control sequence using Eq. 9 is not convenient. In the following it will be shown that some simplifications can be made without relevant prejudice of precision on path tracking.

Superposition of the minimization horizon

The superposition of the minimization horizon, the so called "receding horizon", reduces the error in the transition between segments and have the advantage, relevant in terms of control quality, that disturbances are recognized much earlier, and can so be compensated in the next minimization. If the computed *m* signals were used, disturbances that occur in the segment could be considered only in the next computation [3].

The Receding Horizon Approach. The control law for the new minimization after each step can be obtained from the complete minimization over *m* steps using just the first value of the computed sequence:

$$u_s(k) = [1 \quad 0 \quad \cdots \quad 0]\mathbf{u}_s(k) \,. \qquad (10)$$

Usually when guiding a robotic manipulator by sensors only position reference is available (is captured), velocity and acceleration must be derived from samples of the position reference. Using a second order numerical differentiation for the reference velocity and acceleration results a compact form for the ***FMP*** control law, Eq. 11, which can be visualized by the block-diagram in **Figure 2**.

$$u_s(k) = \sum_{\nu=-1}^{m+2} a_\nu w(k+\nu) - \sum_{\nu=1}^{3} m_{x1}(\nu) x_\nu(k). \; (11)$$

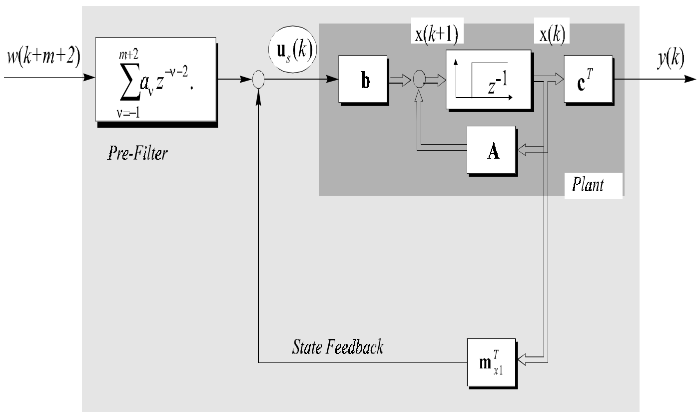

Figure 1 – Following Modell Predictive (FMP) Servocontroller.

Simulation for a typical trajectory

The simulation of the ***FMP*** servo-control for the nominal linearized robot joint described by

$$F(s) = \frac{13824}{s^3 + 72s^2 + 1728s + 13824} \,,$$

and a typical trajectory is shown in **Figure 2**. The reference signal *w* and the output of the plant *y* are almost identical as seen in fig. 1-a. The small residual error can be seen in fig. 1-d. As expected, in the vicinity of reference velocity discontinuities occurs a greater error.

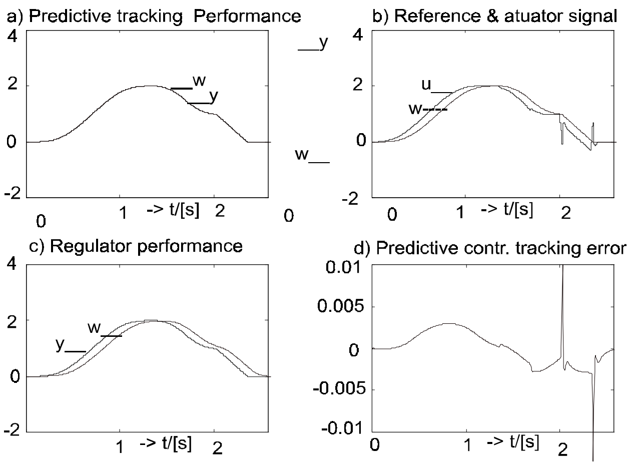

Figure 2 - Simulation of *FMP servocontroller*.

When only the nonlinear decoupling controller with state space feedback is used (system described by Eq. 1) we have a pronounced tracking error, **Figure 2-c**. **Figure 2-b** shows that the ***FMP*** servo-controller produces a control signal that "foresees" (predict) the plant lag dynamics, so enabling the minimization of the trajectory error.

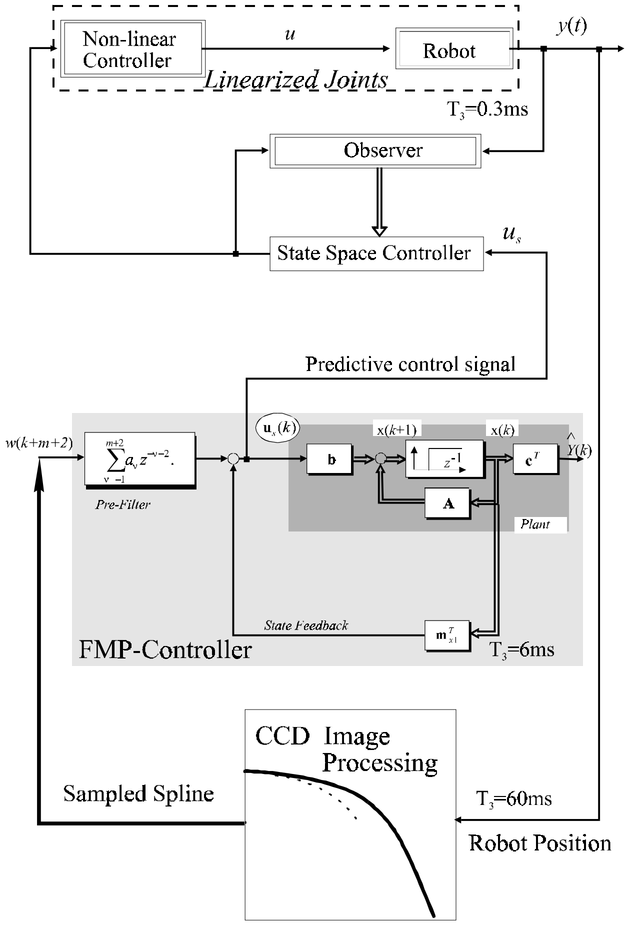

Figure 3 - *FMP* control of CCD guided robot.

Experimental results

The industrial automation has experienced a fast evolution due to the great development of digital techniques. An adequate mathematical apparatus combined with powerful digital processing equipment permits nowadays control complex tasks, e.g., hydraulic driven robotic manipulators with the precision demanded by the manufacturing industry. These, which for long time had been considered as "very difficult" to be controlled because of their extremely non-linear characteristics, have newly attracted research interest. The great power density of the hydraulic drive leads to very advantageous robot weight-load ratio (typically 1:5 when electrical driven robots have a ratio of approx. 1:100).

The implemented control scheme, **Figure 3**, shows the ***FMP*** controller as a feed-forward channel, that allows ***separation*** of path tracking and disturbance rejection characteristics. The slower nonlinear and state space control of the robot is designed for disturbance rejection, while the reference tracking is enhanced by the fast predictive dynamic of the ***FMP*** controller. As a stable system by itself, the feed-forward ***FMP*** filter will not affect the stability of the robot joint control scheme.

To verify the theoretical ***FMP*** algorithm results, a hydraulic manipulator guided by a CCD-video camera [3], [8], as shown in **Figure 5,** was used.

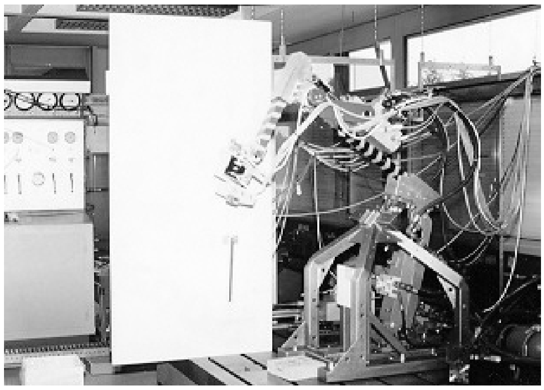

Figure 4-Hydraulic manipulator guided by a CCD-camera.

The trajectory to be followed by the robot was printed on paper and attached to the trajectory panel. After finding an border the control scheme guide the robot along this border with a pre-established TCP velocity.

The non-linear decoupling controller was implemented on an AT&T DSP32C processor in a PC host. Two DSP16A and a DSP32C in another PC host carried out the image interpretation and the FMP servocontrol. A monochrome DALSA Inc® 128x128 pixel camera, with 16MHz dot clock, required the project of a custom high-speed frame-grabber.

From each image 10 border points in tracking direction are extracted. After a path length parameterization and a transformation in joint coordinates a spline fitting is employed. This analytical spline is then sampled to furnish new trajectory points to the ***FMP*** as suggested in **Figure 5.**

Circle form test. For characterization of positioning precision and repeatability of working machines and industrial manipulators, the Circle Form Test is frequently used [7]. By this test the joints are so moved that couplings and friction effects, particularly for slow motions, can be evidenced,
Figure 5**.**

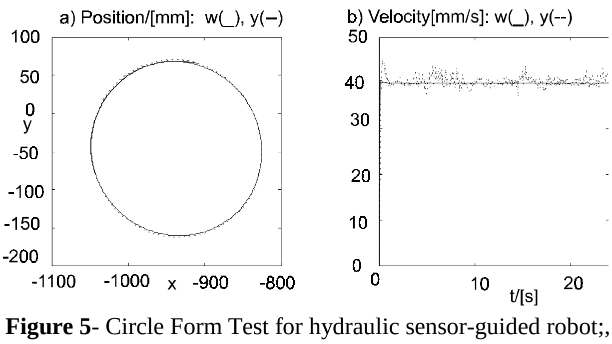

Figure 5- Circle Form Test for hydraulic sensor-guided robot;, Reference velocity is vref = 40 mm/s.

CCD-camera guided weld robot

To investigate sensor-guided robots in welding cells, the experimental apparatus shown in **Figure 6** and **Figure 7** was assembled at GRACO. A monochrome Pulnix CCD video camera was attached to the welding torch and captures look-ahead trajectory information.

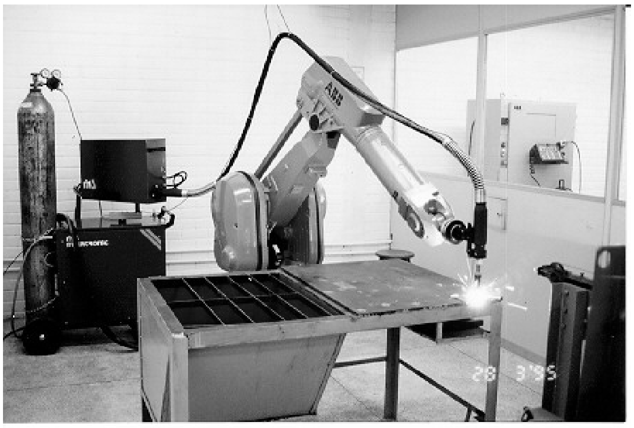

Figure 6- Weld robot at GRACO/UnB - Brasilia.

A Laser diode led equipped with prismatic lens, also attached to the weld torch, projects a light plane at 45° relative to the welding torch axis. So the junction of the metal parts to be welded can be easily identified by a simple image processing. First results of the CCD guided weld robot has been obtained. Greater difficulties lay currently in the not open interface with the industrial robot being used. Further research activities will be taken to improve the robot guiding system.

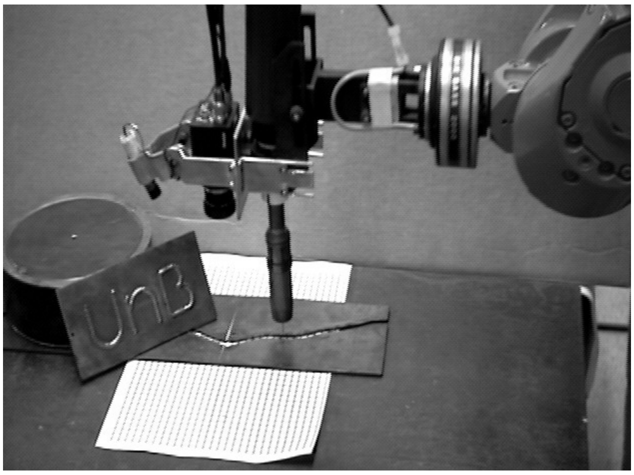

Figure 7-CCD-guided weld robot at GRACO, detail view.

Conclusion

By the inclusion of the future (sensor captured) path and a reference trajectory generator model the ***FMP*** algorithm represents a generalization of traditional predictive algorithms. It uses *all* state space information available, from the plant and from the trajectory generator model. This guarantees the stability of the proposed scheme *by construction*, as the equivalence to a discrete LQR problem has shown in [8].

For linearized robotic joints modeled as 3*rd* order systems, a *spline generator model* was used. If the sensor captured trajectory is indeed a *spline,* the theoretically (not considering uncertainties) tracking error will be zero. For generic trajectories, that should be considered in welding cells, the proposed approach represents the possible reducing of tracking error. In this case the *FMP*-controller approximates the trajectory by the *spline* segments that the robot can better follow.

The implementation of the proposed servocontroller on a CCD-guided hydraulic robot demonstrates the practical relevance of the ***FMP*** algorithm. The dynamic tracking error, a crucial factor to guarantee quality in automated robot welding, was almost eliminated. The residual errors observed in the measures are mainly due to friction in the hydraulic cylinders. This is just a matter of technological restriction of that kind of drives, which demands constructive issues to reduce their influence.

References

[1] S.C.A. Alfaro, A. Bauchspiess, V.H. Casanova Alcalde, R.H. van Els, L.R. Soares Jr, M.H. Suguieda: *Conception and development of an integrated welding cell,* 8-JOM, Helsingør, Denmark, May 11-14 (1997)

[2] B.Anderson and J. Moore: *Optimal Control - Linear Quadratic Methods*. Prentice-Hall, Canberra (1989)

[3] A.Bauchspiess: *Prädiktive sensorgesteuerte Bahnführung von Handhabunssystemen*, PhD Thesis, in german, University Erlangen-Nürnberg (1995)

[4] E. Freund: Decoupling and Pole Assignment in nonlinear Systems, Electronic Letters 9, pp. 373-374 (1973)

[5] A. Isidori: *Nonlinear Control Systems*, 2ed Springer (1989)

[6] R. Keyser: *Basic Principles of Model Predictive Control*. ECC'91, Grenoble, pp. 1753-1758 (1991)

[7] U. Piechottka, W.M. Grimm, F. Berlin, N. Becker: *Verwendung von Stögrößenmodellen zur Verbesserung des Regelverhaltens*, Teil 2. **at** 12/94, pp. 525-532 (1994)

[8] F. Rehfeld: *Der Einsatz linear quadratischer Optimierungs-verfahren zur sensorgesteuerten Bahnfuehrung*, Diplomarbeit, University Erlangen-Nbg (1995)

[9] R. Soeterboek: *Predictive Control - A Unified Approach*, Prentice Hall, London (1992)

[10] C. Wurmthaler: *Prozeßmodelle als Grundlagen moderner Regelungskonzepte*, University Erlangen-Nürnberg (1994)