3. Conclusions We propose a constructive solution for the generation of collision-free trajectories between two points in an environment containing multiple obstacles in a d-dimensional space. This builds on the geometry of the obstacles and the convex lifting procedure describing a graph around the obstacles. This graph represents a key element in order to generate collision-free trajectories employing MPC controllers with recursive feasibility guarantees and convergence in between an initial and a final position.

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ADAPTIVE SENSORLESS INDUCTION MOTOR CONTROL SYNTHESIS WITH QUADRATIC COST CRITERIA

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The sensorless (without speed sensor) induction motor vector control synthesis is an actual problem [1] for industrial applications. This paper proposes a modified cost criterion which improve the speed computation, based on model reference adaptive control (MRAC).

In the stationary frame (a, b) the induction motor with the state vector $x = (\Psi_a, \Psi_b, i_a, i_b)^T$ and the control vector (u_a, u_b) is described by the equations

$$\begin{aligned}
\dot{\Psi}_a &= -\alpha\Psi_a - \bar{\omega}\Psi_b + \alpha L_1 2 i_a,\\
\dot{\Psi}_b &= -\alpha\Psi_b + \bar{\omega}\Psi_a + \alpha L_1 2 i_b,\\
\frac{di_a}{dt} &= -R_1 K_4 i_a + K_4 u_a - k_2 K_4 \dot{\Psi}_a,\\
\frac{di_b}{dt} &= -R_1 K_4 i_b + K_4 u_b - k_2 K_4 \dot{\Psi}_b,\\
y &= i_{ab}.
\end{aligned} \tag{1}$$

The electromagnetic torque depends on the current vector (i_a, i_b) and the flux vector as follows:

$$M = k_M(\Psi_a i_b - \Psi_b i_a). \qquad (2)$$

There are the unknown, not measured speed $\bar{\omega}$ and the flux vector $[\Psi_a, \Psi_b]$ to be computed from the system's measurable output $y = i_{ab} = (i_a, i_b)$. So, the induction motor equations (1), (2) can be considered as a model for the speed and flux computing. Let $\hat{y} = \hat{i}_{ab} = (\hat{i}_a, \hat{i}_b)$ be the model output, then $e = (\hat{i}_{ab}) - y$ is the system tracking error. All the variables from the model are marked with $(\wedge)$.

The conventional gradient method [2] is based on form $V = x^T \Lambda x$, minimization, with the state vector error x. However, this approach has some disadvantages, if the flux vector is not measurable. The improved criterion to minimize is as follows

$$V = (\hat{i}_a - i_a)^2 + \hat{i}_b - i_b)^2 + \lambda(\hat{M} - M)^2, \qquad (3)$$

where $(\hat{M} - M)^2$ contributes to the flux and current oscillation reduction. The Lyapunov function V derivative takes a form

$$\dot{V} = 2(\hat{i}_a - i_a)\frac{d(\hat{i}_a - i_a)}{dt} + 2(\hat{i}_b - i_b)\frac{d(\hat{i}_b - i_b)}{dt} + 2\lambda(\hat{M} - M)(\dot{\hat{M}} - \dot{M}). \qquad (4)$$

Therefore, its gradient is determined by the expression

$$\nabla_{\hat{\bar{\omega}}}\dot{V} = 2(\hat{i}_a - i_a)\frac{\partial}{\partial\hat{\bar{\omega}}}\frac{d\hat{i}_a}{dt} + 2(\hat{i}_b - i_b)\frac{\partial}{\partial\hat{\bar{\omega}}}\frac{d\hat{i}_b}{dt} + 2\lambda(\hat{M} - M)\frac{\partial\dot{\hat{M}}}{\partial\hat{\bar{\omega}}}. \qquad (5)$$

In order to make the Lyapunov function (3) decreasing, the estimated speed must satisfy the resulting equation

$$\dot{\hat{\bar{\omega}}} = -\Gamma\nabla_{\hat{\bar{\omega}}}\dot{V}.$$

The expression (5) must realize the adaptation such as the model dynamics becomes similar to the induction motor dynamics. In equation (5) Γ is a positive constant.

The sensorless model reference adaptive vector control simulation is executed for 2.2 KW induction motor. The simulation demonstrates the successful speed estimation with (3)-(5).

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INPUT RECONSTRUCTION PROBLEM UNDER THE LACK OF INFORMATION IN A QUASI-LINEAR STOCHASTIC EQUATION

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1. Problem Statement. The problem of reconstructing unknown inputs in a quasi-linear stochastic differential equation (SDE) is investigated on the basis of the approach of the theory of dynamic inversion suggested in the works by Kryazhimskii, Osipov, and their colleagues, see [1] and its bibliography. We consider the statement when the simultaneous reconstruction of disturbances in the deterministic and stochastic terms of the equation is performed with the use of discrete incomplete information on a number of realizations of the stochastic process. The work actually continues studies [2], where a similar problem was solved for a linear SDE via a partially observed system of linear ordinary differential equations (ODEs) obtained by the method of moments.

A SDE with diffusion depending on the phase state is of the form

$$dx(t,\omega) = (A(t)x(t,\omega) + B(t)u_1(t) + f(t))\,dt + U_2(t)\,x(t,\omega)\,d\xi(t,\omega). \quad (1)$$

Here, $t \in T = [0, \vartheta]$, $x \in \mathbb{R}^n$, $x(0,\omega) = x_0$ is a known deterministic or random (normally distributed) vector; $\omega \in \Omega$, (Ω, F, P) is a probability space, $\xi(t,\omega) \in \mathbb{R}$ is a standard scalar Wiener process; $A(t)$, $B(t)$, and $f(t)$ are continuous matrix functions of dimension $n \times n$, $n \times r$, and $n \times 1$, respectively. Two external disturbances act on the system: vectors $u_1(t) \in \mathbb{R}^r$ and $u_2(t) \in \mathbb{R}^n$ (the main diagonal of a diagonal matrix $U_2(t) \in \mathbb{R}^{n\times n}$) with values from given convex compact sets; both functions are of bounded variation. The input u_1 enters into the deterministic term and influences the mathematical expectation of the desired process, whereas the vector u_2 regulates the amplitude of random noises.