Robust Control of Excavation Mobile Robot with Dynamic Triangulation Vision

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Abstract: The problem of control system synthesis for excavation works autonomous mobile robot on the basis of the game approach is considered. Vision function and spatial orientation of the robot is realized by the dynamic triangulation laser vision system. It is assumed that the real state of the object belongs to the certain set of potential states in the form of polyhedron. Simulation results and functional ability analysis for the proposed control system are concluded.

1 INTRODUCTION

Progress of autonomous mobile robots for excavation works (EMR) is stimulated with numerous applications in various areas of human activities. Such robots are equipped by bulldozer blade and should in autonomous mode rid the area of obstacles, profile surface along the dead-reckoning track, etc.

One of the key challenges in application of EMR is navigation in environments that are densely cluttered with obstacles and has a rough terrain. The challenge of an intelligent control system in mobile robot navigation it is caused by uncertainties associated with sensory systems and the dynamic environment. It causes various approaches (Lamon, 2007; Selekwa, 2008) to this task solution. However, none of them still not reach a complete solution enough for full scale industrial manufacturing of such robot. The key problem is a proper mutual complementation of a sensory systems and corresponding robust control algorithm.

2 PROBLEM FORMULATION

For EMR performance have to get an environment model, define self location inside, plan its trajectory and operate blade and, at the same time, functioning in a changeable environment. The critical particular features of EMR are: work time and the guaranteed accuracy.

The main methods which are used in EMR control synthesis at uncertainty conditions is fuzzy logic (Selekwa, 2008) and self-organizing neural networks (Miller, 1996). But peculiarity of EMR functioning reduce efficiency of such control systems use. The initial set of the postulated fuzzy rules may be incomplete or contradictory, and the kind and parameters of membership functions that describe system's variables may reflect reality not quite sufficiently. The use of adaptive neuronetwork control systems is criticality limiting the requirement of operating time, and it becomes crucial.

The game approach guarantees that processes will remain satisfactory at any sets of uncertain factors. In our opinion, it is expedient for robust control to use the next pair: 1) sensory system providing real time continuous feedback in Cartesian coordinates, and 2) control system based on the game approach (Eryemenko, 2009).

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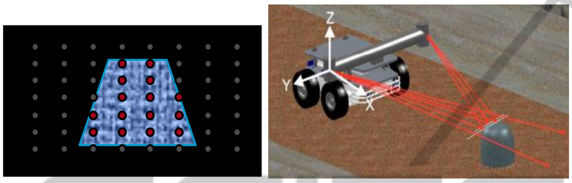
3 SENSORY SYSTEM FOR ENVIRONMENT MODEL

In literature is known only unique technical vision system (TVS) which can provide the environment model in Cartesian coordinates in real time, or a system with digital mapping of the obstacles surface in fixed field-of-view. Its detailed description is given in (Sergiyenko, 2009; Rivas, 2008; Sergiyenko and Hernandez, 2009). Its general view is given on Fig.1.



a) b)

Figure 1: TVS Operation principle: a) isometric view; b) digital mapping of visible obstacle surface.

Each point highlighted on the obstacle surface (Fig.1,*b*) by laser beam of is called S_{ij}. For each S_{ij} are obtained X,Y, and Z Cartesian coordinates set by formulas presented in (Sergiyenko, 2009; Rivas, 2008; Sergiyenko and Hernandez, 2009). The accuracy of coordinates measurement is not uniform (Fig. 2) in field-of-view, but in the olive- and green-zone correspondingly it is not more than 1% and 4% out of level of confidence (Rivas, 2008; Sergiyenko and Hernandez, 2009). Usually, modern regular step drives are operated with average velocity of 1 KHz, so we can obtain coordinates at least of 1000 points per second, each X, Y, and Z with metrological accuracy and known uncertainties. This is a point to apply this TVS as input data sensory system (Sergiyenko, 2009; Rivas, 2008; Sergiyenko and Hernandez, 2009) for game approach control (Eryemenko, 2009; Gurko, 2011) realization.

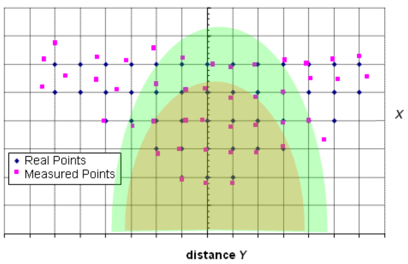


Figure 2: TVS field-of-view and “accuracy zones”.

4 CONTROL OBJECTIVE

Given is the uncertain discrete-time system

$$X_{n+1} = AX_n + BU_n + CF_n\,, \tag{1}$$

where $X_n \in R^m$, $n = 0,1,\dots, N$, is the state vector; $U_n \in R^q$, $n = 0,1,\dots, N - 1$, is the control vector; $F_n \in R^r$, $n = 0,1,\dots, N - 1$, is the input disturbance vector; A, B, C are matrixes of corresponding dimensions, n – sampling time, $n = 0,1,2,\dots$ (instances of: TVS interrogation/ control action implementation).

Available to the controller are measurements of the form

$$Y_n = X_n + Z_n,\ n = 0,1,\dots, N-1 \tag{2}$$

where $Y_n \in R^s$ is the measurement vector; $Z_n \in R^v$ is the measurement noise vector.

About vectors F_n and Z_n it is known only that are belongs to prescribed guaranteed bounded sets

$$F_n \in \Omega_n^F,\ Z_n \in \Omega_n^Z,\ \forall n \ge 0. \tag{3}$$

According to the game approach to the optimal control of uncertain dynamic system the controller on each sampling step n has to solve the following task

$$\min_{U_n \in \Omega_n^U}\ \max_{F_n \in \Omega_n^F}\ \max_{Z_n \in \Omega_n^Z} \left\{\omega\left(X_n, U_n, F_n, n\right)\right\}, \tag{4}$$

where Ω_n^U is a given set of control actions; $\omega(\cdot)$ is a specific losses function:

$$\omega(\cdot) = V\left(X_{n+1}, n\right) + \tilde{\omega}\left(X_n, U_n, n\right), \tag{5}$$

where $V(\cdot)$ is Lyapunov function, $\tilde{\omega}(\cdot)$ is a given function, defines control costs and assigns limitations on their value.

Relate to EMR control task of the advantage of the considered approach is in the following. Using the model (1) and equations (2) and (3) at each sampling step $n > 0$ the set Ω_n^X of possible EMR’s states is carried out and the control U_n solving problem (4) is defined. The main problem is identification of set Ω_n^X of the object possible states taking to account external disturbances and noise in sensing system.

5 CONTROL DETERMINATION

For simplicity we will consider 2D case, when U_n

and F_n in (1) and Z_n in (2) are scalar quantities. Note, that with increasing of object order, the procedure described below does not change. About F_n it is known that it satisfies the constrain $-\delta \le f_n \le \delta$, where δ is any rational number. Measurement of space orientation of the robot is carried out with a noise Z_n, $-\varepsilon \le Z_n \le \varepsilon$, where ε is any rational number.

For 2D case the state vector $X_n = [X_n^1, X_n^2]$; the observable output (a robot's angle of yaw) $Y_n = [X_n^1, 0]$. The control U_n is determined by the following algorithm.

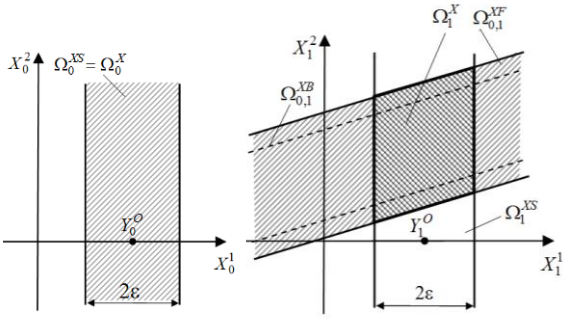
1. At $n = 0$ the output value Y_0 is measured. The state estimation is not a point value but a set of admissible states due to measurement noise, and to unknown rate of coordinate X_1 changes. This set is located in a vertical dashed bar $\Omega_0^{XS} = \Omega_0^X$ which is symmetric concerning the measured value Y_0^O of the object output Y_0 and bounded with parallel X_0^2 axis lines (see Fig. 3 *a*).

2. The control U_0^O action should move the object from the state X_0 into a state X_1. But since the object's actual state is unknown, the set of its possible states at the moment n=1 is defined as follows. The set Ω_0^X is being reflected at coordinate system X_1^1, X_1^2 with the matrix A of eq.(1). The new set $\Omega_{0,1}^X$ contains those states, in which the control object can get starting from Ω_0^X in a self movement.

The set $\Omega_{0,1}^X$ is moved along the vector $B = (b_1, b_2)$ on U_0^O value, thus the set $\Omega_{0,1}^{XB}$ will be generated (see Fig. 3*b*). It's a forecast of the EMS possible states after control U_0^O action, but in absence of disturbance F_0.

3. Disturbance F_0 leads to the transformation of the set $\Omega_{0,1}^{XB}$ to the set $\Omega_{0,1}^{XF} \subseteq \Omega_{0,1}^{XB}$ with the vector C. The set $\Omega_{0,1}^{XF}$ is a set of the object's predictable states at n = 1, taking into account existing control U_0^O together with disturbance F_0.

4. The next set Ω_1^X of system potential states at n = 1 have been computed as a result of intersecting: $\Omega_1^X = \Omega_1^{XF} \bigcap \Omega_1^{XS}$, where the set Ω_1^{XS} is an infinite bar, that 2ε wide and symmetrical relative $X_1^1 = Y_1^O$.



a) b)

Figure 3: a) Set Ω_0^X; b) Set Ω_1^X.

5. The U_1 is evaluated to solve the task (4).

6. The set Ω_2^X is been built in a similar manner. The previous set Ω_1^X is moved with the control U_1, transformed with the vector C and is intersected with a bar of new observation Ω_2^{XS}, and further the procedure iteratively repeats.

6 NUMERICAL EXAMPLE

Consider the example of control definition that based on mentioned algorithm. Let EMR's dynamic describes by difference equations (1) and (2) with next parameters

$$A = \begin{bmatrix} 0.9822 & 0.2125 \\ -0.0893 & 0.7120 \end{bmatrix}; \ B = \begin{bmatrix} 0.0281 \\ 0.2125 \end{bmatrix}.$$

Let's consider also disturbance F_n is pulsed and satisfy the constrain $|F_n| \le \delta = 0.025$. Consider the optimal value of the cost function (6):

$$J = \min \sum_{n=0}^{\infty} \left(X_1^2(n) + X_2^2(n) + 0.5U^2(n) \right), \qquad (6)$$

The MATLAB solution of the given task is presented above on Figs. 4-6. The Fig. 4 shows a graphics of system's output Y_n, disturbance F_n, and control U_n that minimized the function (6) value. Fig. 5 shows the values of measurement noise. It was assumed that the measurement noise is in the foregoing range $|F_n| \le 0.025$ and is subject to a uniform distribution law. On Fig. 6 the area of possible states Ω_n^X at steady state (n=30) is presented.

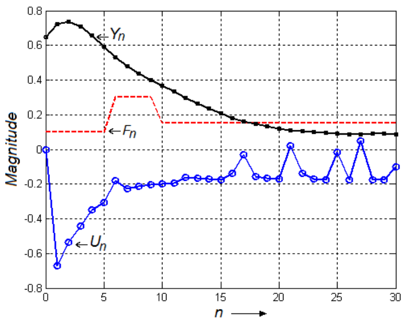


Figure 4: Graphics of: a) modification of system output Y_n, disturbance F_n and control U_n.

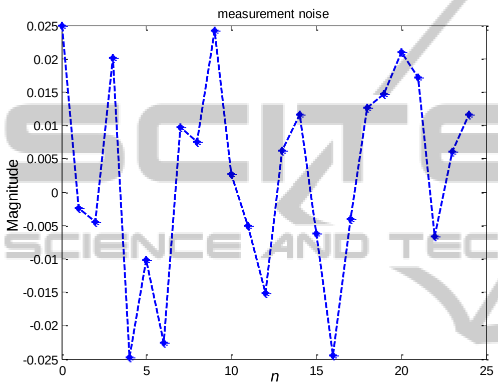


Figure 5: The measurement noise.

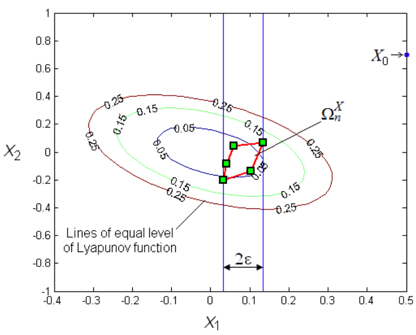


Figure 6: Set Ω_n^X of potential EMR's states at n=30.

As evident from Fig. 4-6 the proposed controller ensures enough control quality. For system quality improvement it is necessary to use the observer giving a specified multiple rating of possible perturbations at each control step.

7 CONCLUSIONS

In this paper we considered the problem of robust control of EMR. The unique technical vision system for EMR's sensory system, providing real-time continuous feedback in Cartesian coordinates, was proposed. A new algorithm was given for the state filtering for robust control determination.

The presented algorithm allows intersect convex polyhedrons. As the actual systems are nonlinear, it is necessary to be able to intersect non-convex sets. It is an objective for future work. Also expedient to note that additional increase of technical vision resolution in future can be reached by implementation of our original method of scales binding described in (Sergiyenko, 2011).

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