

Predictive Model of Sensor Readings for a Mobile Robot

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Abstract—This paper presents a predictive model of sensor readings for mobile robot. The model predicts sensor readings for given time horizon based on current sensor readings and velocities of wheels assumed for this horizon. Similar models for such anticipation have been proposed in the literature. The novelty of the model presented in the paper comes from the fact that its structure takes into account physical phenomena and is not just a black box, for example a neural network. From this point of view it may be regarded as a semi-phenomenological model. The model is developed for the Khepera robot, but after certain modifications, it may be applied for any robot with distance sensors such as infrared or ultrasonic sensors.

Keywords—Mobile robot, sensors, prediction, anticipation.

I. INTRODUCTION

MODELS of mobile robots usually takes into account only their kinematics and dynamics. Then variables describing the state of the mobile robot are: location coordinates, direction (azimuth) and sometimes velocity. In such models usually readings from the distance sensors are not taken into account. Such measurements, describing the distance from obstacles, are utilized only during generation of the control signals (velocities of the wheels). Moreover, only present measurements are used without any anticipation of measurements. Such anticipation may improve the control quality. If, for example, during the so called behavioral control the “avoid obstacles” rule is activated if the sensory reading exceed assumed threshold, then the control signals might be improved based on the anticipation of the sensory readings.

In the literature several attempts of anticipation of sensory readings are reported but they are not serve during the control of the robot but for selection of landmarks [3]. For example in articles [2] and [5] an artificial feedforward neural network was proposed as a predictor of further measurements of sensors. The proposed predictor was very simple – it contained only one layer and took as inputs only past readings from neighbouring sensors and did not use wheel velocities of the mobile robot. Such simplified model was good enough for the landmark selection based on the difference between the predicted and real readings but for the control purposes a

more accurate model is needed. In work [6] a more precise model consisting the recurrent neural network was presented.

In this paper we propose the predictive model of sensory readings for the Khepera robot [4]. This model is developed on the basis of the physical phenomena (kinematics of the robot and the sensor characteristics) and takes into account velocities of the wheels.

The article is organized as follows: in Section 2 the phenomenological model for one sensor is developed under certain assumptions. In Section 3 the previous considerations are generalized for multi-sensory robot. Section 4 presents the method of identification of proposed model. Finally Section 5 presents numerical results of identification and validation of the model.

II. MODEL DEVELOPMENT FOR ONE SENSOR

Let us consider the simplest situation when a robot with only one sensor approaches the obstacle (wall) with the velocity v as presented in Fig. 1. The distance between the sensor and the wall is denoted by l .

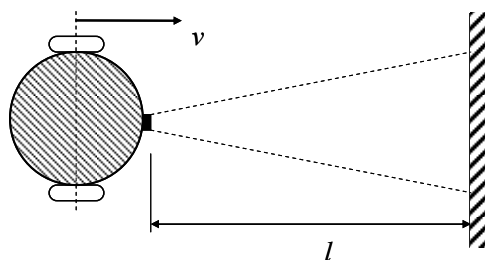


Fig. 1 The simplified case for one sensor

The signal from the sensor s is a function of the distance l :

$$s = F(l) \quad (1)$$

according to the sensor characteristics. An example of such characteristics is presented in Fig. 2.

The derivative of s w.r.t. time is as follows:

$$\frac{ds}{dt} = \frac{ds}{dl} \cdot \frac{dl}{dt} = F'(l) \cdot v \quad (2)$$

Let us assume that the sensor characteristics (1) is a

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monotonic function. Then we may write a formula for the distance l as follows:

$$l = F^{-1}(s) \quad (3)$$

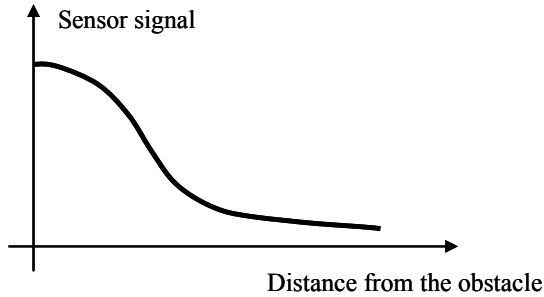


Fig. 2 Example of sensor characteristics

From (2) and (3) we have

$$\frac{ds}{dt} = F'(F^{-1}(s)) \cdot v \quad (4)$$

Substituting in (4) the expression $F'(F^{-1}(s))$ by a new function $g(s)$ finally we obtain

$$\frac{ds}{dt} = g(s) \cdot v = f(s, v) \quad (5)$$

The function $f(s, v)$ has a multiplicative form where one of multipliers is the velocity v . It is quite reasonable because if the robot does not move ($v = 0$) then s should not change. The only thing is to find the function $f(s, v)$ or equivalently $g(s)$. It could be found based on $F(l)$ but we assume that it is unknown. Instead on this in this paper we try to approximate the function $f(s, v)$ choosing its multiplicative form with respect to v .

The differential equation (5) can now serve as a predictive model for the sensor reading. Knowing the sensor reading for present time t one can simulate (5) for the period $(t, t + \Delta t)$ and find a prediction of the sensor reading at time $t + \Delta t$.

III. MODEL DEVELOPMENT FOR MULTI-SENSOR ROBOT

In this paper we develop a model for Khepera robot which is schematically presented in Fig. 3. The robot has two wheels which velocities are v_L and v_R respectively. It has eight sensors with readings (signals) s_0 up to s_7 .

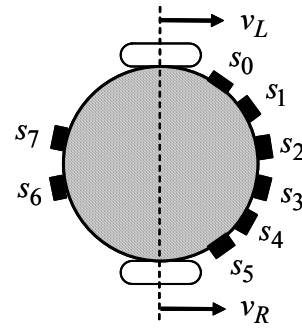


Fig. 3 Khepera robot

The predictive model of the sensors for the Khepera robot, in contrary to the model obtained in previous Section, will take into account two velocities v_L and v_R . Moreover, we assume that the model for sensor number i depends also on neighbouring sensors number $i-1$ and $i+1$.

Hence, the general form of the model for i th sensor is as follows:

$$\frac{ds_i}{dt} = f_i(s_{i-1}, s_i, s_{i+1}, v_L, v_R) \quad (6)$$

The model (6) may be presented in a block-diagram form, see Fig. 4. We examine several possible structures of the function $f_i(\cdot)$ and we chose a function quadratic with respect to s_i and linear with respect to s_{i-1} and s_{i+1} :

$$\begin{aligned} \frac{ds_i}{dt} = & v_L \cdot [a_{i1} \ a_{i2} \ a_{i3} \ a_{i4} \ a_{i5}] \cdot \begin{bmatrix} 1 \\ s_i \\ s_i^2 \\ s_{i-1} \\ s_{i+1} \end{bmatrix} + \\ & + v_R \cdot [a_{i6} \ a_{i7} \ a_{i8} \ a_{i9} \ a_{i10}] \cdot \begin{bmatrix} 1 \\ s_i \\ s_i^2 \\ s_{i-1} \\ s_{i+1} \end{bmatrix} \end{aligned} \quad (7)$$

In above equation velocities v_L and v_R are multipliers as in the model for one sensor (5) and for $v_L = v_R = 0$ the output of the model (7) is constant.

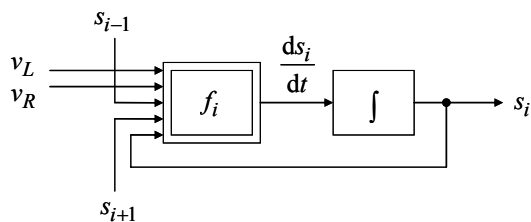


Fig. 4 Block diagram of the model for one sensor

IV. MODEL IDENTIFICATION

The model developed in previous Section contains 80 parameters $a_{ij}; i=1,2,\dots,8, j=1,2,\dots,10$. To identify the model we need to find their optimal values based on the data collected during identification experiment. The data contains sensor readings $s_i; i=1,2,\dots,8$ and velocities v_L and v_R recorded at discrete time moments $\{0, h, 2h, 3h, \dots, Nh\}$ where h is the sampling time and $N+1$ is the total number of samples.

There are several possible ways to identify the parameters. The problem of identification is not trivial because the model is non-linear. Fortunately, the task can be solved using Least Squares (LS) method.

Let us write equation (6) where the left side is replaced by backward-difference estimator of the derivative:

$$\frac{s_i(t) - s_i(t-h)}{h} = f_i(s_{i-1}(t), s_i(t), s_{i+1}(t), v_L(t), v_R(t)) \quad (8)$$

For one sensor we may write N such equations for $t = h, 2h, 3h, \dots, Nh$. The right side of considered model (7) is linear with respect to parameters $a_{ij}; i=1,2,\dots,8, j=1,2,\dots,10$ so it can be solved by Least Squares (number of equations is much greater than number of parameters). The approach is illustrated in Fig. 5.

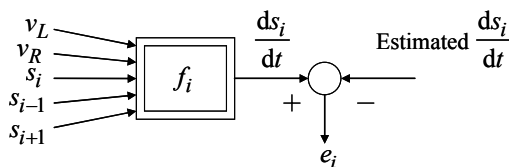


Fig. 5 The idea of identification: the minimized error is the difference between derivatives of the sensor reading taken from the model and estimated from the data

V. IDENTIFICATION AND VALIDATION RESULTS FOR KHEPERA ROBOT

The model proposed in Section III has been identified with the method presented in previous Section. We collected two data sets: identification and a validation data set. Time of the identification experiment was 250 seconds and time of the validation experiment was 100 seconds. During both experiment the robot moved in environment with obstacles and walls using the Breitenberg's algorithm [1]. Velocities of both wheels and signals from all eight sensors were recorded with sampling time $h = 0.1$ [s].

The model (7) with parameters estimated based on the identification data set was tested on the validation data set. Below we present validation results. Fig. 6 presents velocities of wheels during the validation experiment. The next three Figures contain sensory readings and their prediction for only one, 6th sensor.

The prediction for time horizon $\Delta t = 0.5$ [s] is presented in Fig. 7 by dotted line. Solid line represents the true (recorded) signal from the sensor. In fact the dotted line is a result of many simulations (for 0.5 [s]), each starting from true readings of all sensors. In other words: it tells us how the signal from the sensor has been predicted 0.5 [s] before.

Fig. 8 presents predictions for longer time horizon 1[s]. One can observe that the differences are bigger than before. This is obvious: the longer is the prediction time horizon the bigger are differences. Selected parts on both graphs, for times 40-50[s] are presented in Fig. 9.

VI. CONCLUSION

In this paper we proposed the predictive model of sensory readings for a mobile robot. The model is developed for the Khepera robot but it may be applied to any mobile robot with distance sensors such as infrared or ultrasonic sensors. The model is semi-phenomenological which means the structure of the model takes into account the physical phenomena. The model contains parameters which are estimated based on experimental data. The model is non-linear but it is possible to estimate parameters using LS method.

Numerical results of identification (based on the learning data) and validation (based on the test data) showed that the prediction of the model is satisfactory for time horizon of about 1 second which is enough long for control purposes. In the future work the model presented in this paper will be used in behavioral control framework. We expect that use of the prediction of the sensory readings may improve the control quality. We also plan to test different forms of the nonlinear function of (6) keeping the velocities as multipliers. For example a multi-layer perceptron may be used and learned using standard backpropagation algorithm.

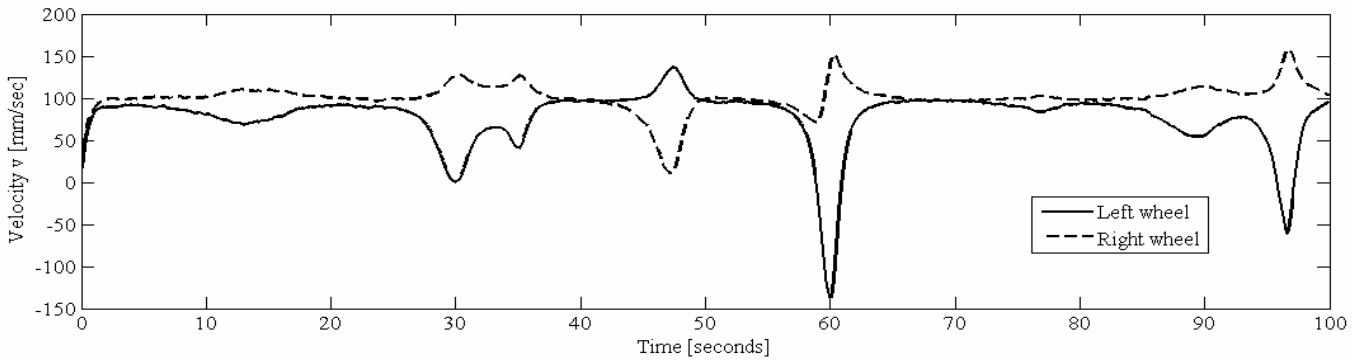


Fig. 6 Wheel velocities during the validation experiment

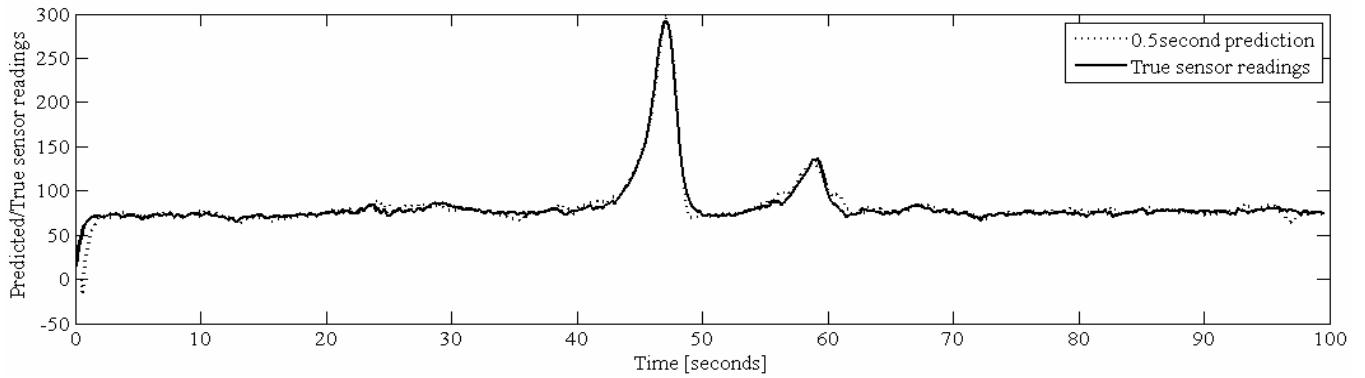


Fig. 7 Predicted vs true sensor readings for one sensor during the validation experiment, prediction horizon = 0.5 second

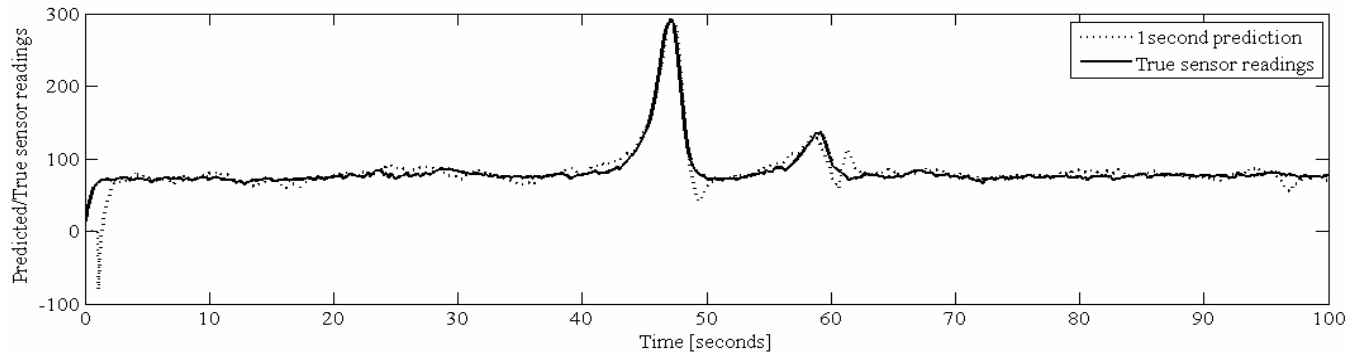


Fig. 8 Predicted vs true sensor readings for one sensor during the validation experiment, prediction horizon = 1 second

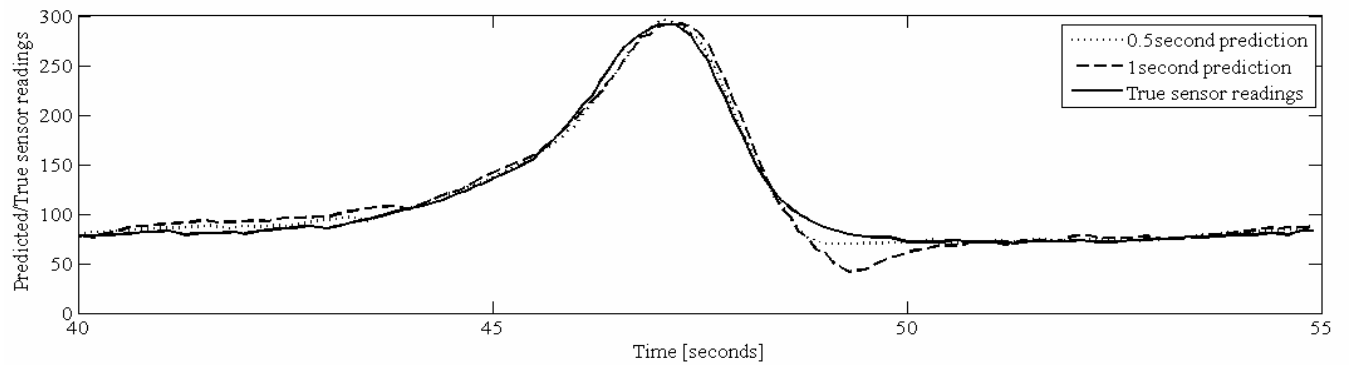


Fig. 9 Predicted vs true sensor readings for one sensor during selected time interval of the validation experiment (from 40 to 55 seconds)

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