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ROBOTIC SEWER PIPE MAPPING CONCEPT – SIMPLIFIED 2D CASE PRELIMINARY STUDY

Krejsa J.[1], Věchet S.[2]

Abstract: *Sewer pipes mapping is a task of creating the virtual model of pipe system using either external means or internal sensor of a robot moving through the pipe. The paper introduces the concept of such mapping algorithm based on fusion of data given by internal sensors on multi-segment robot both on the segments themselves and the inter-segment sensors. The fusion is based on Extended Kalman Filter (EKF) and is shown for simplified 2D model. The simulation results for simplified model show good robustness against the noise.*

Keywords: Pipe mapping, extended Kalman filter, robotic mapping, SLAM

1. Introduction

Pipelines are irreplaceable mean of transportation of gases and liquids. It is prone do damage and aging and therefore the inspection and cleaning of pipelines is a necessity. Moreover, in some cases the construction maps are not reliable and as most of the pipes are buried underground and inaccessible, finding where the pipes are actually located is of essence.

There are basically two approaches for the mapping problem: using a surface sensors and using the in-pipe robots. In some cases the approaches can be combined, e.g. using ground penetrating radar and robotic camera, as shown by Li (2020). Most real life conditions, however, require in-pipe robots. There the approaches also differ, as diameter of the pipe plays essential role in robot design. For larger diameters the task is simpler (see Hansen 2015), for smaller diameters the design is somewhat limited. Very good review of current approaches can be found in Kazeminasab (2021). The mapping itself is well reviewed in Aitken (2021). This paper focuses on sewer pipe mapping using only the internal rotational sensors of the robot and introduces simplified 2D version of the concept to prove its viability.

2. The concept

Our design concept of a mapping (and possibly inspection/cleaning) robot consists of multiple rigid segments interconnected via rotational joints. Each segment is equipped with inertial measuring unit (IMU), supplying the attitude and heading reference system (AHRS). Inter-segment connections supply the relative angle between rigid segments. Those signals are fused together to produce the angular description of the robot. There are some basic assumptions and consequences of those assumptions utilized further in the data processing:

- The pipe system is static (there is no motion of the pipe system related to the origin of global coordinate system).
- As the pipe system is static, each segment of the robot have to sequentially get to the position of previous segments.
- There is no lateral motion of segments withing the pipe (perpendicular to the pipe axis), only the motion along the pipe direction is considered.

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[1] Assoc. Prof. Ing. Jiří Krejsa PhD, Institute of Thermomechanics of the Czech Academy of Sciences, Brno department, Czech Republic, krejsa@fme.vutbr.cz

[2] Assoc. Prof. Ing. Stanislav Věchet, PhD, Institute of Thermomechanics of the Czech Academy of Sciences, Brno department, Czech Republic, vechet.s@fme.vutbr.cz

The main idea of the mapping concept is as follows: The orientation of the first segment (in the direction of motion within the pipe) after the motion step is performed is unknown, therefore it is considered in the previous direction (we simply have no means from internal sensors mentioned above to determine otherwise). When the motion step for given length is performed, the following segments have to travel in the same path as the previous ones. The state of the robot is given by the position of the head and both AHRS angles in each segment and the relative angles between them. The estimate of the state of the robot is calculated using Extended Kalman Filter, with the only action being the motion step distance and angles serving as the measurement. Please note that the head position course (that corresponds to estimated trajectory) is calculated in correction step of EKF and necessarily accumulates position errors.

3. Simplified 2D case

In order to quickly test the idea, we have reduced the dimensionality of the problem to 2D case. Therefore each segment can be represented by a single angle, the interconnection angle between two segment also by a single angle and head position by 2 coordinates.

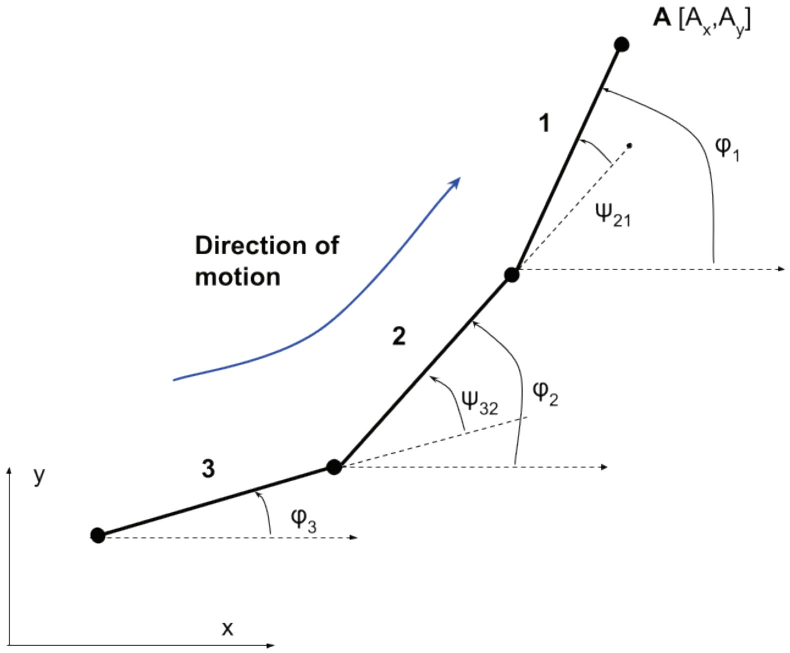

Fig. 1: Segments of the robot and both absolute and relative angles of and between the segments. Point A represents front side of the first segment (the head) of the robot.

3.1. State estimation model

Standard notation of EKF is used in following text. The state vector for the robot with N segments consists of head position, attitude angles and relative angles, as denoted in (1).

$$\mathbf{x} = \left[A_x, A_y, \varphi_1, \varphi_1, \dots \varphi_N, \psi_{21}, \psi_{32}, \dots \psi_{N-1\,N}\right]^T \tag{1}$$

where A is the head of the robot, φ_1 is the first segment attitude and ψ_{21} is the relative angle between the first and second segment. The measurement $\mathbf{y}_k$ at the time step k consists of all the angles, therefore the state model is linear in its second part, as shown in (2)

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, \mathbf{u}_k, k) + \mathbf{v}_k \tag{2}$$

$$\boldsymbol{y}_k = \mathbf{H}_k \mathbf{x}_k + \boldsymbol{w}_k \tag{3}$$

where function *f* represents the motion model, $\mathbf{u}_k$ is the action, in our case the rectilinear motion of the first segment expressed by the distance travelled and $\mathbf{v}_k$, $\mathbf{w}_k$ are the process and measurement noises.

During the prediction phase the motion model was established in following manner. The first segment moves towards its original attitude (that is our best guess, as the trajectory in front of the robot is unknown). The subsequent segments move towards its original attitude, then its front end is transferred to the end of preceding segment resulting in new attitude of the segment. When the length of the segment is equal to the distance travelled, the motion model is further simplified, as shown in (3) for the robot with 3 segments.

$$\boldsymbol{x}_{k+1} = \begin{bmatrix} A_x \\ A_y \\ \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \psi_{21} \\ \psi_{32} \end{bmatrix} = f(\boldsymbol{x}_k, \boldsymbol{u}_k) = \begin{bmatrix} A_x + Lcos\varphi_1 \\ A_y + Lsin\varphi_1 \\ \varphi_1 \\ \varphi_1 \\ \varphi_2 \\ 0 \\ \psi_{21} \end{bmatrix} \tag{4}$$

where L is the length of the segment.

The k-th prediction step of EKF is then

$$\hat{\mathbf{x}}_{k+1|k} = f\left(\hat{\mathbf{x}}_{k|k}, \mathbf{u}_k, k\right) \tag{5}$$

$$\mathbf{P}_{k+1|k} = \mathbf{F}_k \mathbf{P}_{k+1|k} \mathbf{F}_k^T + \mathbf{V}_k \tag{6}$$

where covariance matrix **P** is calculated using partial derivatives **F** of function f $\boldsymbol{F}_k = \frac{\partial f}{\partial x}\Big|\boldsymbol{x} = \hat{\boldsymbol{x}}_{k|k}$.

The estimate of process noise **V** is the highest for the first three variables, as the position and angle of the first segment are subject of higher uncertainty because the upcoming path of the pipe is unknown.

The correction step of EKF is linear, as all the measured variables are present in the state vector, therefore

$$\hat{\boldsymbol{x}}_{k+1|k+1} = \hat{\boldsymbol{x}}_{k+1|k} + \boldsymbol{K}_{k+1}\tilde{\boldsymbol{y}}_{k+1}$$
$$\boldsymbol{P}_{k+1|k+1} = \boldsymbol{P}_{k+1|k} - \boldsymbol{K}_{k+1}\boldsymbol{H}_{k+1}\boldsymbol{P}_{k+1|k}$$

where

$$\tilde{\boldsymbol{y}}_{k+1} = \boldsymbol{y}_{k+1} - \boldsymbol{H}_{k+1}\hat{\boldsymbol{x}}_{k+1|k}$$

$$\boldsymbol{S}_{k+1} = \boldsymbol{H}_{k+1}\boldsymbol{P}_{k+1|k}\boldsymbol{H}_{k+1}^T + \boldsymbol{W}_{k+1}$$

$$\boldsymbol{K}_{k+1} = \boldsymbol{P}_{k+1|k}\boldsymbol{H}_{k+1}^T\boldsymbol{S}_{k+1}^{-1}$$

The estimate of measurement **W** depends on the expected precision of attitude estimates, matrix **H** that relates the state and the measurement is trivial.

3.2. Simulation results

Above-described model was implemented in Matlab and simulations with a number of trajectories, segment sizes and noise levels in the measurement variables were performed. An example of comparison of real and estimated trajectory (pipe shape) is shown in Fig. 2. Uniform distribution of the noise in angular readings was used. This figure shows two estimates, the first one, denoted *low noise*, has angular noise limited to ± 2 degrees; while the second one, denoted high noise, has ± 15 degrees range.

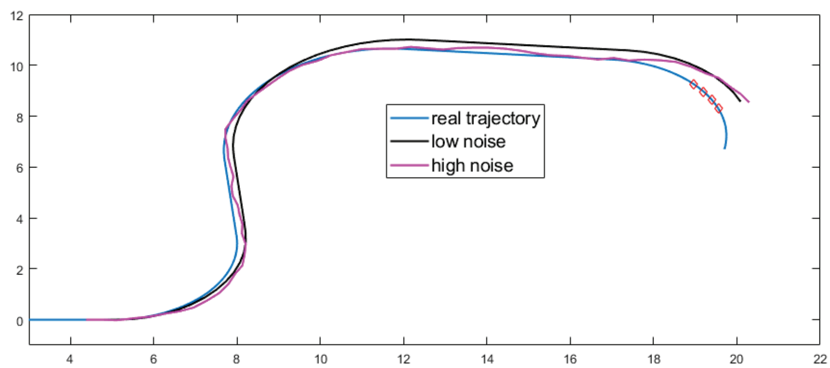

Fig. 2: Comparison of real (blue) and estimated trajectory for different levels of measurement noise. The red diamond shapes represent the end points of robot segments.

The comparison of the real angle of the first segment of the robot, its noisy measurement and resulting estimate from EKF is shown in Fig. 3. One can see that even for high values of the angular noise the corrected estimate is in reasonable values, considering that for the first segment the prediction model does not have any prior information about the angle change.

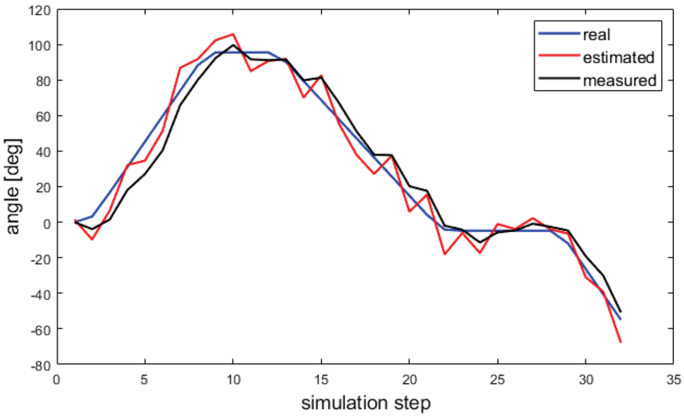

Fig. 3: Comparison of real (blue), measured and estimated angle of the first segment of the robot.

The noise was considered to have zero mean, however, simulations with nonzero mean for φ_1, φ_2 and φ_3 were also performed, as one might expect the offset to be present in those angles readings, contrary to relative angles between segments. As the method in general produces accumulated errors with larger diameters in pipe elbows compared to reality, the influence of the nonzero mean heavily depends on the actual shape of the real trajectory.

4. Conclusions and future work

We have presented the concept of the robotic sewer pipe mapping, using only the internal angular sensors of multisegmented robot. The simulation results proved the usability of the approach. While the estimated trajectory of the robot (and subsequently the resulting pipe map) inevitably deteriorates during the motion, as no external sensor is present, the influence of the sensor reading noise is lower than expected. This encourages further exploration of the concept. First the extension to 3D case with the absolute attitude of segments estimated form IMU using independent Kalman (or complementary) filter. We have already done some experiments with real HW on this matter, but it is not in this paper due to lack of space. Secondly the usage of general knowledge about the sewer pipe systems, as it consists of straight elements and standardized elbows. Such information can be used to pipe map postprocessing. And lastly in most practical cases the robot has to return back to its original position. When switching the head and tale of the robot, the map of the return motion can be processed the same way as the forward way and the difference of the original and final position can be utilized the same way as closed loop problem in traditional mobile robot mapping task.

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