FUZZY ODOMETRY ERROR APPROXIMATION OF A MOBILE ROBOT

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Abstract: This paper presents a non-systematic odometry error qualificatory method base on fuzzy logic. Odometry is the most widely used navigation method for mobile robot positioning. It is well known that odometry provides good short-term accuracy, is inexpensive, and allows very high sampling rates. The disadvantage of odometry is that the position error grows without bound unless an independent reference is used periodically to reduce the error. We have started a research project that works out some intelligent methods for calculate the plausibility of odometric trajectory and pose of a mobile robot.

Keywords: Robotics, Fuzzy Logic, Odometry.

1. INTRODUCTION

Odometry is the most widely used navigation method for mobile robot positioning. It is well known that odometry provides good short-term accuracy, is inexpensive, and allows very high sampling rates. However, the fundamental idea of odometry is the integration of incremental motion information over time, which leads inevitably to the accumulation of errors. Particularly, the accumulation of orientation errors will cause large position errors which increase proportionally with the distance traveled by the robot. Despite these limitations, most researchers agree that odometry is an important part of a robot navigation system and that navigation tasks will be simplified if odometric accuracy can be improved.

In this paper we present an odometry error approximation algorithm, which based on fuzzy logic. This method uses only internal references and do not need other external absolute or relative measurement.

2. DEAD RECKONING AND ODOMETRY

Dead reckoning (derived from “deduced reckoning” of sailing days) is a simple mathematical procedure for determining the present location of a vessel by advancing some previous position through known course and velocity information over a given length of time [Dunlap and Shufeldt, 1972]. The vast majority of land-based mobile robotic systems in use today rely on dead reckoning to form the very backbone of their navigation strategy, and like their nautical counterparts, periodically null out accumulated errors with recurring “fixes” from assorted navigation aids.

The most simplistic implementation of dead reckoning is sometimes termed odometry; the term implies vehicle displacement along the path of travel is directly derived from some onboard “odometer.” A common means of odometry instrumentation involves optical encoders directly coupled to the motor armatures or wheel axles.

This method uses encoders to measure wheel rotation and/or steering orientation. Odometry has the advantage that it is totally self-contained, and it is always capable of providing the vehicle with an estimate of its position. The disadvantage of odometry is that the position error grows without bound unless an independent reference is used periodically to reduce the error [Cox, 1991].

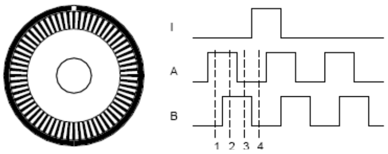
Odometry is used in almost all mobile robots, for various reasons:

- Odometry data can be fused with absolute position measurements to provide better and more reliable position estimation [Cox, 1991; Hollingum, 1991; Byrne et al., 1992; Chenavier and Crowley, 1992; Evans, 1994].
- Odometry can be used in between absolute position updates with landmarks. Given a required positioning accuracy, increased accuracy in odometry allows for less frequent absolute position updates. As a result, fewer landmarks are needed for a given travel distance.
- Many mapping and landmark matching algorithms (for example: [Gonzalez et al., 1992; Chenavier and Crowley, 1992]) assume that the robot can maintain its position well enough to allow the robot to look for landmarks in a limited area and to match features in that limited area to achieve short processing time and to improve matching correctness [Cox, 1991].
- In some cases, odometry is the only navigation information available; for example: when no external reference is available, when circumstances preclude the placing or selection of landmarks in the environment, or when another sensor subsystem fails to provide usable data.

2.1. *Incremental Optical Encoders*

The simplest type of incremental encoder is a single-channel tachometer encoder, basically an instrumented mechanical light chopper that produces a certain number of sine- or square-wave pulses for each shaft revolution. Adding pulses increases the resolution (and subsequently the cost) of the unit. These relatively inexpensive devices are well suited as velocity feedback sensors in medium- to high-speed control systems, but run into noise and stability problems at extremely slow velocities due to quantization errors [Nickson, 1985]. The tradeoff here is resolution versus update rate: improved transient response requires a faster update rate, which for a given line count reduces the number of possible encoder pulses per sampling interval. A very simple, do-it-yourself encoder is described in [Jones and Flynn, 1993]. More sophisticated single-channel encoders are typically limited to 2540 lines for a 5-centimeter (2 in) diameter incremental encoder disk [Henkel, 1987].

In addition to low-speed instabilities, single-channel tachometer encoders are also incapable of detecting the direction of rotation and thus cannot be used as position sensors. Phase-quadrature incremental encoders overcome these problems by adding a second channel, displaced from the first, so the resulting pulse trains are 90 degrees out of phase as shown in Figure 1. This technique allows the decoding electronics to determine which channel is leading the other and hence ascertain the direction of rotation, with the added benefit of increased resolution.



State	Ch A	Ch B
S_1	High	Low
S_2	High	High
S_3	Low	High
S_4	Low	Low

Fig. 1. Phase-quadrature incremental encoder

3. SYSTEMATIC AND NON-SYSTEMATIC ODOMETRY ERRORS

Odometry is based on simple equations that are easily implemented and that utilize data from inexpensive incremental wheel encoders. However, odometry is also based on the assumption that wheel revolutions can be translated into linear displacement relative to the floor.

This assumption is only of limited validity. One extreme example is wheel slippage: if one wheel was to slip on, say, an oil spill, then the associated encoder would register wheel revolutions even though these revolutions would not correspond to a linear displacement of the wheel.

Along with the extreme case of total slippage, there are several other more subtle reasons for inaccuracies in the translation of wheel encoder readings into linear motion. All of these error sources fit into one of two categories: systematic errors and non-systematic errors.

3.1. *Systematic Errors*

Systematic errors are particularly grave because they accumulate constantly.

Sources of systematic errors:

- Unequal wheel diameters.
- Average of actual wheel diameters differs from nominal wheel diameter.
- Actual wheelbase differs from nominal wheelbase.
- Misalignment of wheels.
- Finite encoder resolution.

- Finite encoder sampling rate.

In this work we do not concentrate to systematic error because it is corrected fairly well.

3.2. Non-Systematic Errors

The sources of non-systematic errors:

- Travel over uneven floors.
- Travel over unexpected objects on the floor.
- Wheel-slippage due to:
    - slippery floors.
    - overacceleration.
    - fast turning (skidding).
    - external forces (interaction with external bodies).
    - internal forces (castor wheels).
    - non-point wheel contact with the floor.

The problem with non-systematic errors is that they may appear unexpectedly (for example, when the robot traverses an unexpected object on the ground), and they can cause large position errors.

4. MEASUREMENT OF NON-SYSTEMATIC ERRORS

It is noteworthy that many researchers develop algorithms that estimate the position uncertainty of a dead-reckoning robot (e.g., [Tonouchi et al., 1994; Komoriya and Oyama, 1994].) With this approach each computed robot position is surrounded by a characteristic “error ellipse,” which indicates a region of uncertainty for the robot's actual position (see Figure 2.) [Tonouchi et al., 1994; Adams et al., 1994].

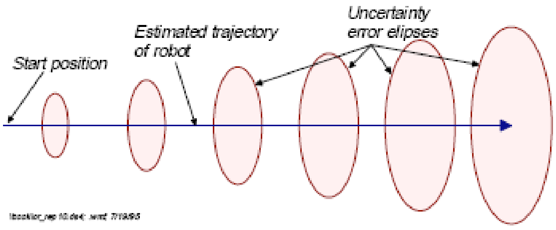


Fig. 2. Growing “error ellipses” indicate the growing position uncertainty with odometry. (Adapted from [Tonouchi et al., 1994].)

In our research work we worked out a multi level fuzzy inference system for approximation of uncertainty in odometry error.

5. FUZZY LOGIC

When the new concept of fuzzy sets and fuzzy logic was proposed by Zadeh [Zadeh, 1965], he was motivated by control and systems engineering aspects. Conventional control theory can cope with only a restricted class of systems, where linear, or at least, analytical input-output models can be constructed, or obtained by the eventually numerical, approximative solutions of the partial differential equation system describing the connection between input and output state variables (those being often dependent from each other).

Fuzzy logic has a great advantage in comparison with discrete formal logical systems: it can approximate very well, it is suitable for the construction of approximative models that have any desired degree of exactness- or inexactness, and, by giving up the absolute goal of obtaining exactly optimal solutions, it is suitable for the construction of computationally effective algorithms of reasoning and control [Kosko, 1992]. However, it is important to note at this point that good approximation does not necessarily mean precise approximation; in many applicational contexts, it is better to approximate as roughly as the concrete problem on hand allows it as preciseness of the approximation usually must be traded off for convenient computability (both in the sense of space and time complexity).

6. FUZZY ODOMETRY ERROR APPROXIMATION

Calculate or guess the odometry error, without any references, is very difficult task. There is not any precise and elegant method.

We looked for a method which need not any external references, can approximate the odometry error with appropriate accuracy by internal signals and parameters. However, it is important to note at this point that good approximation does not necessarily mean precise approximation.

We work out a hierarchical fuzzy system for calculate the odometry error, it means the measure and the type of the error. Our system has two level of approximation, one symmetric for both wheel and second which collect and synchronise the wheel data.

In the base level we use two fuzzy error approximators (FOA – Fuzzy Odometry Approximator), one for each driving wheel.

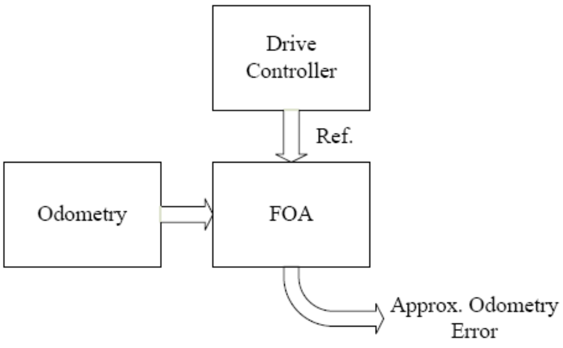


Fig. 3. Wheel odometry error approximator

One of these subsystems collects the pre-processed odometric data from the incremental encoder and uses the drive controller's manipulated value as internal reference. The synchronisation block collects the time data and synchronise the fuzzy inferences for calculate the width of odometry error.

By the help of appropriate rule base in this level we get information about the running of the wheel. The state of the wheel may be smooth running, locking, slipping and spiking. These inferences are available on both driving wheels from time to time. The Figures 4 - 6. show the fuzzy sets of the drive references, the odometry data and the output approx. odometry error and error type.

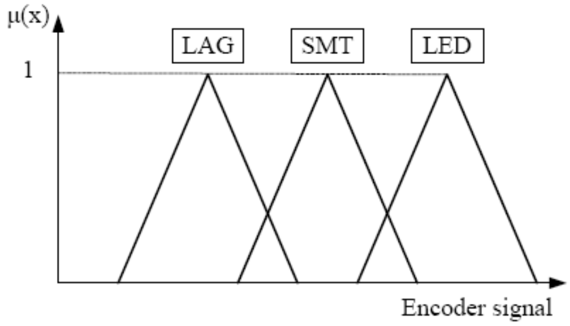


Fig. 4. The input fuzzy variable of one encoder

Table 1 Encoder input fuzzy variable

Term	Definition
LAG	encoder signal lagging
SMT	encoder signal smooth
LED	encoder signal leading

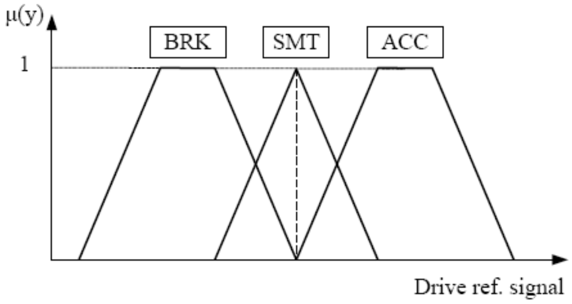


Fig. 5. The input fuzzy variable of one drive reference signal

Table 2 Reference input fuzzy variable

Term	Definition
BRK	motor breaking
SMT	motor smooth running
ACC	motor accelerating

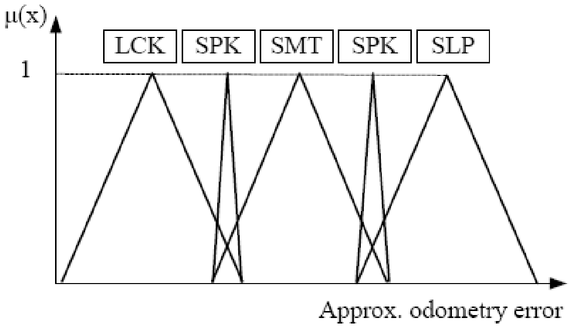


Fig. 6. The input fuzzy variable of one drive reference signal

Table 3 Reference input fuzzy variable

Term	Definition
LCK	lock error type
SPK	spike error type
SMT	smooth running
SLP	slip error type

On the second level the approx. odometry errors of the two wheels are passed to FPA, Fuzzy Pose Approximator, with the synchronic signals. The FPA infers the pose error (localisation and orientation) from these data and the a-priory knowledge.

The full pose error approximation system is shown in Figure 7.

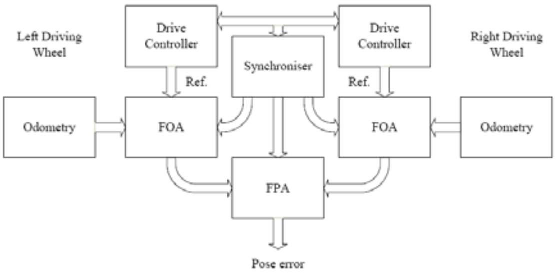


Fig. 7. The input fuzzy variable of one encoder

7. CONCLUSION

In this paper we present an odometry error approximation algorithm, which based on fuzzy logic. This method uses only internal references and do not need other external absolute or relative measurement.

Since it is an approximation with fuzzy inference algorithms it does not give a precise error calculation, but we can reach a very good estimation on odometry error and pose of the mobile robot.

The method provides really good results in indoor using on smooth surface. On rough environment the approximation need more complex calculation or other references.

In the future we have the intention of working out an odometry error clearing method base on the above process.

8. ACKNOWLEDGEMENT

This work was supported by the Hungarian Scientific Research Fund (OTKA) under Grant T049499 “Developing intelligent control strategies for autonomous mobile robots in logistic systems”.

REFERENCES

Adams, M. et al., 1994, “Control and Localisation of a Post Distributing Mobile Robot.” *1994 International Conference on Intelligent Robots and Systems (IROS '94)*, Munich, Germany, Sept. 12-16, pp. 150-156.

Byrne, R.H., Klarer, P.R., and Pletta, J.B., 1992, “Techniques for Autonomous Navigation.” *Sandia Report SAND92-0457*, Sandia National Laboratories, Albuquerque, NM, March.

Chenavier, F. and Crowley, J., 1992, “Position Estimation for a Mobile Robot Using Vision and Odometry.” *Proceedings of IEEE International Conference on Robotics and Automation*, Nice, France, May 12-14, pp. 2588-2593.

Cox, I.J., 1991, “Blanche - An Experiment in Guidance and Navigation of an Autonomous Mobile Robot.” *IEEE Transactions Robotics and Automation*, 7(3), pp. 193-204.

Dunlap, G.D. and Shufeldt, H.H., 1972, *Dutton’s Navigation and Piloting*, Naval Institute Press, pp. 557-579.

Evans, J. M., 1994, “HelpMate: An Autonomous Mobile Robot Courier for Hospitals.” *1994 International Conference on Intelligent Robots and Systems (IROS '94)*. Munich, Germany, Sept. 12-16, pp. 1695-1700.

Gonzalez, J., Stentz, A., and Ollero, A., 1992, “An Iconic Position Estimator for a 2D Laser RangeFinder.” *Proceedings of IEEE International Conference on Robotics and Automation*, Nice, France, May 12-14, pp. 2646-2651.

Henkel, S.L., 1987, “Optical Encoders: A Review.” *Sensors*, September, pp. 9-12.

Hollingum, J., 1991, “Caterpillar make the earth move: automatically.” *The Industrial Robot*, Vol. 18, No. 2, pp. 15-18.

Jones, J.L. and Flynn, A., 1993, *Mobile Robots: Inspiration to Implementation*. ISBN 1-56881-011-3, A K Peters, Ltd. Wellesley, MA.

Komoriya, K. and Oyama, E., 1994, “Position Estimation of a Mobile Robot Using Optical Fiber Gyroscope (OFG).” *International Conference on Intelligent Robots and Systems (IROS '94)*. Munich, Germany, Sept. 12-16, pp. 143-149.

Kosko, B., 1992, Fuzzy systems are universal approximators. in *Proc. IEEE Int. Conf. Fuzzy Syst.* pp. 1153-1162, San Diego, CA.

Nickson, P., 1985, “Solid-State Tachometry.” *Sensors*, April, pp. 23-26.

Tonouchi, Y., Tsubouchi, T., and Arimoto, S., 1994, “Fusion of Dead-reckoning Positions With a Workspace Model for a Mobile Robot by Bayesian Inference.” *International Conference on Intelligent Robots and Systems (IROS '94)*. Munich, Germany, Sept. 12-16, pp. 1347-1354.

Zadeh, L.A., 1965, Fuzzy Sets. *Inform. Contr.*, vol. 8, pp. 338-353.