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Uncertainty-Aware Sensor Fusion in Sensor Networks

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Summary:

Uncertainty assignment for measurement values is a common process for single sensors, but this procedure grows in complexity for sensor networks. Often measured values are processed further in such networks and uncertainty must be evaluated for virtual values. A simple example is the fusion of homogeneous values and faulty or drifting sensors can harm the virtual value. We introduce a method from the field of key-comparison into the domain of sensor fusion. The method is evaluated in three different scenarios within an agent-framework.

Keywords: sensor networks, sensor fusion, measurement uncertainty, digital twin, emulated sensor

Motivation

Sensors always have some degree of uncertainty in the values they provide. This uncertainty can be related to time and/or measurement. As the number of sensors increase, for example in cases of large sensor networks, the accumulated uncertainty grows as well. In our previous work [1] uncertainty propagation was part of the use cases described, in particular within the context of sensor fusion. Sensor fusion is the combination of sensory data such that the resulting information is better than those obtained from individual sensors [2]. Sensor fusion is especially important for capturing industrial processes in the form of a digital twin. In our project FAMOUS[1], digital twins are virtual representations of sensors and sensor networks in the fields of discrete manufacturing and process engineering. There is plethora of literature that use statistical and stochastic models to address uncertainty in sensor fusion [3, 4, 5, 6]. This paper presents methods to reduce the effect of failing/drifting sensors and evaluates the uncertainty [7] in sensor fusion by drawing parallels to key comparison methods in metrology [8].

Uncertainty-Aware Sensor Fusion

The propagation of uncertainties is evaluated according to the formalism of the *Guide to the expression of uncertainties* (GUM) [9]. Suppose N independent measurements $x_1, \dots, x_N$ are taken by sensors and the corresponding uncertainties $u(x_i)$ are known from datasheets. It is of interest to combine these values into a fused value y_{fusion} and evaluate the uncertainty of that using Eq. 1 and Eq. 10 from GUM. A naive approach would use a weighted mean with weights $\gamma_i = \frac{1}{u(x_i)^2}$. With $k = \sum_{i \in I_c} \gamma_i$ this results in

$$y_{fusion} = \frac{1}{k} \sum_{i \in I_c} \gamma_i x_i$$

$$\mathrm{u}(\mathrm{y}_{\mathrm{fusion}})^2 = \sum_{i \in I_c} \left(\frac{\gamma_i}{k}\right)^2 u(x_i)^2$$

The presented homogenous sensor fusion is structurally similar to key comparisons in metrology. We therefore take a method developed by Cox [9] to calculate a more informed fusion value. The procedure uses the same weighted mean as our naive choice but extends it by a χ^2-test to detect outliers. If outliers are detected, the fusion value is recalculated.

Implementation Details

Sensors, sensor datasheet information and sensor fusion are represented as agents within an agent-framework suited for metrological information processing[2]. Raw sensor data is simulated and fed into the datasheet agent. There,

[1] http://famous-project.eu/

[2] https://github.com/bang-xiangyong/agentMET4FOF

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the sensor value is transformed into an SI-unit and uncertainty information is added based on the datasheet. Thereafter, a uniform disturbance is added based on the given uncertainty and the uncertainty is recalculated for the disturbed sensor reading. The simulated sensor is an acceleration sensor of type LIS3DH[3]. Sensor readings are provided in multiples of earth's gravitational "constant" g. Conversion to an SI-unit is necessary. Uncertainty assignment considers variation of gravitation across the earth, non-linearity offset error and ADC-conversion.

$$x_{SI} = a * (x_{raw} + b)$$

$$u(x_{SI})^2 = (x_{raw} + b)^2 * u_a^2 + a^2 * (u_b^2 + u_x^2)$$

If operated at range $\pm 4g$ with 10bit resolution:

$$a = 9.81 \, \frac{m}{s^2} \qquad b = 0 \qquad x_{raw} \in [-4, 4]$$

$$u_a = 0.025 \, \frac{m}{s^2} \qquad u_b = 0.08 \qquad u_x = 0.5 * \frac{8}{2^{10}}$$

Scenarios

We chose three scenarios to evaluate different methods for sensor fusion in networks. We use in every scenario eight sensors that propagate their values to a virtual sensor that aggregates the incoming measurement values and uncertainties to a new *virtual* value. The incoming signal is a sinusoidal function of the time *t*. In the first scenario all sensors work as intended. In the second scenario, one of the sensors fails after $10\,s$ and returns a faulty value of $0\,m/s^2$ for every following measurement. The third scenario simulates a sensor that starts drifting after $5\,s$. The drift increases linearly for the next $10\,s$ where it remains till the end of the scenario.

Evaluation

Fig. 1 compares both presented methods for the drift scenario. The naive approach shows a smaller uncertainty throughout the simulation but is also strongly biased by the drifting sensor. The advanced method by Cox matches the lower uncertainty of the simple method during normal operation of all sensors but adopts a more robust behavior in case of sensor drift – at the cost of a higher uncertainty value of that result.

Conclusion and Future Work

By taking a known methodology from the field of metrology we can provide robust and uncertainty-aware sensor fusion for homogenous sensor networks. Comparing an informed fusion to a rather naive approach shows robust behavior in two anomalous scenarios. Furthermore, the fusion values are assigned a higher uncertainty, if fewer sensors contribute to it (due to outlier removal).

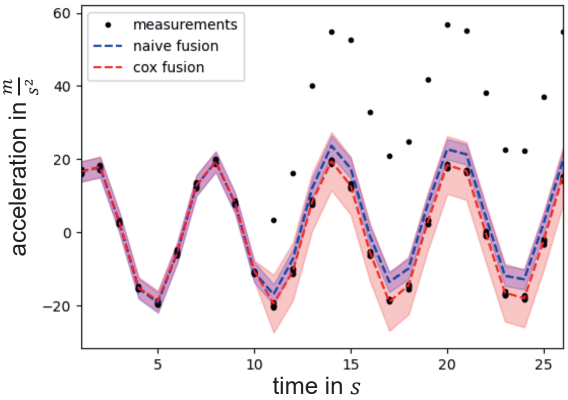

Fig. 1. Comparison of the naive and informed fusion methods with a single drifting sensor. Bands of uncertainties are exaggerated by factor 10 for visualization.

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