Robot visual servoing via Guess Filter

Tristan Cossin[1] and Olivier Strauss[1]

LIRMM, Univ. Montpellier, Montpellier, France, strauss@lirmm.fr

Abstract. In this paper, we propose to use an alternative to the classical Kalman filter (KF) to slave the movement of a robot manipulator to the measurements delivered by a far-infrared reflectometry sensor. This alternative, called Guess filter (GF), uses fuzzy rought set theory and possibilistic inference. It is particularly suited to measurements that are both imprecise and inaccurate. We compare the ability of GF and KF approaches to be used to control a robot on a simulated experience that favors neither approach.

Keywords: Granulation · Filtering · Control · Fuzzy inference.

1 Introduction

The aim of this work is to verify the glue bead assembly of a windscreen in the automotive industry. This could be done by video if the windscreen wasn't obscured by a black strip, the role of which is to protect the glue bead from UV rays. To meet industrial demand, we use a sensor that emits a wave in the far infrared and measures the intensity of this wave after reflection. This is a scanning sensor, which means that at each instant of measurement we have a line of power of reflection measurements as presented in Figure (2). The fundamental assumption in this work is that the glue bead has sufficient continuity to track it with a transverse measurement performed by the sensor.

We use a robot to move the sensor along the bead to measure the bond. As the position of the bead is poorly known, the robot is servo-controlled. The control's role is to deduce, from the measurement at each instant, the transverse position enabling the bead measurement to be maintained at the center of the linear image, and the sensor orientation to be maintained perpendicular to the bead.

The position of the robot end effector that carries the sensor is represented in Figure (1). The glue bend used for this picture has been removed from an assembly for visual inspection.

Figure (2) shows a typical bead measurement situation. Since bonding is carried out on a metal part, there is a large difference between the reflection of the metal substrate and that of the adhesive bead.

The method we use to control the robot is as follows. For each measurement, we estimate the position of the center and the width of the cordon using a watershed method. Since we know the relationship between the pixel measurements and the metric measurements, we can deduce from the position of the

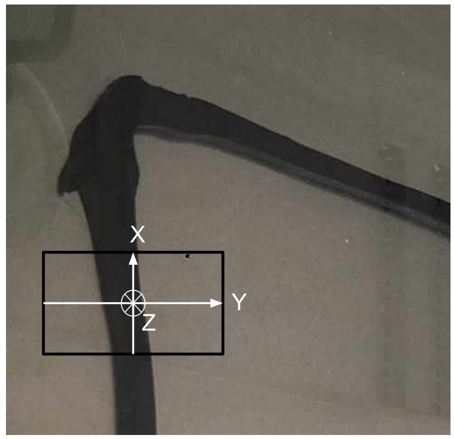

Fig. 1. Frame of the robot effect or w.r.t. the glue bend.

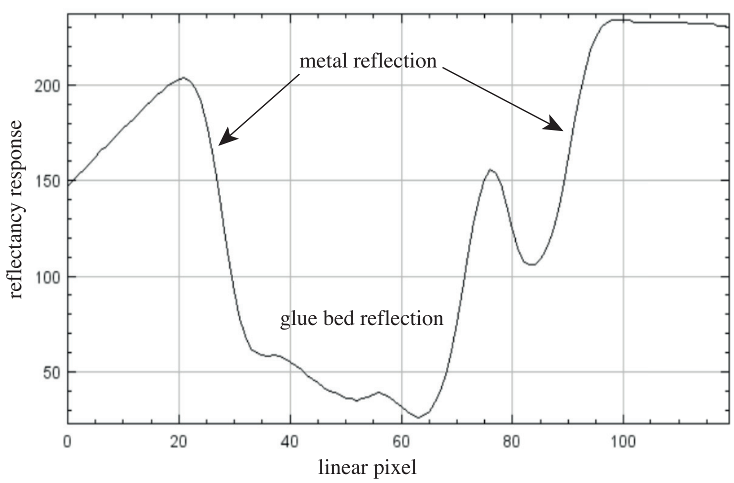

Fig. 2. A measure provided by the sensor.

center of the bead in the image the deviation the robot needs to make to restore this position to the center of the image. For the orientation measurement at a given instant, the ratio between the estimated width of the bead at the previous instant and the measured width at the current instant is used. If this ratio is greater than one, the bead is clearly shrinking. On the other hand, if the ratio is less than one, this may be symptomatic of a change in bead orientation. Let a be the width of the glue bead while b is the width of current measurement of the width – see Figure (3). θ, the angle of rotation to be used to reposition the sensor perpendicular to the bead is such that $a = b.cos(\theta)$. The values of both this angle and the position of the bead center are used to correct the robot's position before the next iteration.

As the measurements involved in this servoing are both imprecise (due to the sampling of the reflection measurement) and uncertain (due to measurement noise), we propose to use a filtering method called Guess Filter (GF) to take this type of condition into account. This filtering approach has been proposed in [5] in the context of estimating the heading of an underwater robot. The work presented in this article differs from the previously cited article in two respects: 1/ estimates from the GF are used directly in the robot's servo loop; 2/ a technique is proposed for estimating a data item that depends non-linearly on the measurements.

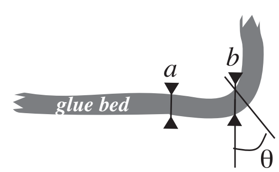

Fig. 3. Angular estimation principle diagrams.

The rest of this article is subdivided as follows. In Section 2, we present a brief overview of the GF and an extension of this method to take into account the situation where the filtered quantity is not measured directly. In Section 3, we present an experiment of the robot servoing process based on filtered measurement, comparing this approach with that using a Kalman filter. We conclude in Section 4.

2 Guess filter

2.1 Some notation

- $\mathbb{R}$ is the real line.
- $\boldsymbol{\rho} \in \mathbb{R}^n$ is a vector of $\mathbb{R}^n$.
- A being a fuzzy subset of $\mathbb{R}$, μ_A is the membership function of A.

2.2 Guess filter principle

The Guess Filter (GF) principle is described in [5]. It is based on the granulation principle defined by Pawlak in his work [4] extended by Dubois and Prade in [1].

Let $\theta(t)$ be a time varying signal. It is assumed that a sensor delivers uncertain, imprecise and discrete measure $m(t)$ of this signal in the form of a random interval M_k where $k \in \mathbb{N}$ is the sample number corresponding to time $t = k.T$, where $T \in \mathbb{R}$ is the sampling period. The aim of the GF is to provide, for each sample, an imprecise estimate $\varTheta_k$ such that $\theta(kT) \in \varTheta_k$ is as probable as possible.

First, let us suppose that θ is a stationary signal, i.e. $\forall t \in \mathbb{R}$, $\theta(t) = a$. If the sensor and the calibration of its imprecision are fully reliable, then $\forall k \in \mathbb{N}$ we have $a \in M_k$. Therefore the best estimate that can be provided concerning the unknown value a at time kT is the set $\varTheta_k = \bigcap_{i=0}^{k} M_i$. In that case precision increases with k. On the other hand, if the sensor or its calibration are unreliable, then a more conservative estimate of a would be the set $\varTheta_k = \bigcup_{i=0}^{k} M_i$. In this dual case reliability increases with k. Naturally, in real life both situations hold. A way to handle this case would be to consider the maximal coherent subsets proposed by [2], i.e. the *best estimate* $\varTheta_k$ can be obtained by a set combinations of the intervals $\{M_i\}_{i=0\ldots k}$.

Now, let us suppose that θ is not stationary but is slowly time varying (*slowly* means that the variation of θ between time kT and $(k+1)T$ is highly lower than the imprecision of the measure M_k). In that case, the influence of interval M_i to obtain the set $\varTheta_k$ should decrease with $(k - i)$.

What is proposed in [5] is to implement this paradigm, somewhat along the lines of the Kalman filter, by proposing a dis-symmetrical combination consisting of updating $\varTheta_k$ with M_{k+1} according to the coherence between $\varTheta_k$ and M_{k+1}. If we stay with a pure ensemblist idea, we could propose the following rule:

$$\varTheta_{k+1} = \begin{cases} \varTheta_k \cap M_{k+1}, \text{ if } \varTheta_k \cap M_{k+1} \neq \varnothing, \\ \varTheta_k \cup M_{k+1}, \text{ otherwise,} \end{cases} \tag{1}$$

$\varnothing$ being the empty set of $\mathbb{R}$.

There are two major drawbacks to this procedure:

1. it quickly becomes algorithmically intractable, as it creates numerous subsets that are difficult to maintain in a coherent representation,
2. it is not nuanced,
3. there is no temporal filtering.

The solution adopted in [5] is to replace a crisp representation of $\varTheta_k$ by a fuzzy representation on the one hand, and to replace an exact representation of the sets by a granulation of this representation on a fuzzy partition *à la Ruspini* on the other hand. This approach makes it possible to combine a purely ensemblistic method with a more statistical method based on votes - as proposed in [6].

On a purely fuzzy level, using the GF consists in calculating the coherence between M_{k+1} and $\varTheta_k$ as being $\pi = Sup_{x\in\mathcal{I}} \min\left(\mu_{\varTheta_k}(x), \mu_{M_{k+1}}(x)\right)$ the possibility of M_{k+1} knowing $\varTheta_k$, computing the conjunction $\varTheta_k \cap M_{k+1}$, the disjunction

$\Theta_k \cup M_{k+1}$ and use an additive modification of the Dubois-Prade updating rule to compute the guessed subset Ψ_{k+1} by:

$$\mu_{\Psi_{k+1}} = \pi.\mu_{\Theta_k \cap M_{k+1}} + (1-\pi).\mu_{\Theta_k \cup M_{k+1}}.$$

Finally use a temporal filtering to compute Θ_{k+1} by:

$$\mu_{\Theta_{k+1}} = \lambda.\mu_{\Theta_k} + (1-\lambda).\mu_{\Psi_{k+1}},$$

$\lambda \in [0,1]$ being a predefined updating factor accounting for the dynamic of the signal to be estimated. For a more thorough explanation of this principle, please refer to the original article.

2.3 Guess filter operating principle

We present here the GF calculation principle. Let us suppose that, by nature, the value of $\theta(t)$ always belong to an interval $\mathcal{I} \subset \mathbb{R}$. Guess filtering requires a fuzzy partition *à la Ruspini* of $\mathcal{I}$. Let $n \in \mathbb{N}$ and $\Omega = \{1,\ldots,n\}$. A fuzzy partition of $\mathcal{I}$ is a family of n fuzzy subsets $\{A_i\}_{i\in\Omega}$ such that:

- $\forall x \in \mathcal{I}$, $\sum_{i\in\Omega} \mu_{A_i}(x) = 1$,
- $\forall i,j \in \Omega$, $i \neq j \implies Sup_{x\in\mathcal{I}} \min\left(\mu_{A_i}(x), \mu_{A_j}(x)\right) < 1$.

The most common solution is to use the so-called triangular fuzzy partition, derived from the translation of a single generative triangular set, as shown in Figure (4). Granulation of a (fuzzy) subset T on the fuzzy partition provides a distribution of n values values gathered in the vector $\boldsymbol{\tau} \in [0,1]^n$ with $\forall i \in \Omega$, $\tau_i = Sup_{x\in\mathcal{I}} \min\left(\mu_T(x), \mu_{A_i}(x)\right)$.

Let us suppose that the granulation of Θ at discrete time k is known as the distribution $\boldsymbol{\theta} = \{\theta_1,\ldots,\theta_n\}$. At discrete time $k+1$, information about s is provided by the sensor in the form of a (possibly fuzzy) interval M. The aim of the iterative procedure is to derive the granulation $\boldsymbol{\theta'}$ of Θ at time $k+1$ based on M and $\boldsymbol{\theta}$.

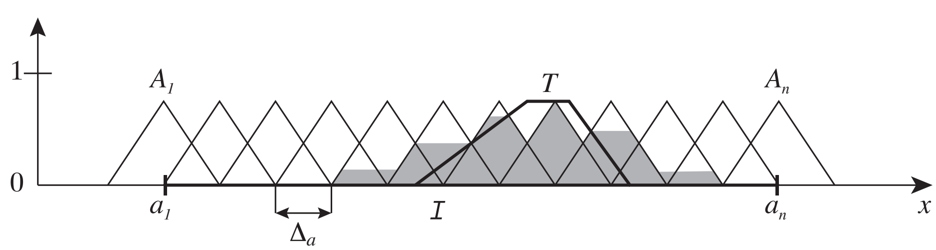

Fig. 4. Granulation of fuzzy set T on a fuzzy partition of I.

After computing of $\boldsymbol{\eta}$, the granulation of M on the fuzzy partition, updating $\boldsymbol{\theta}$, i.e. computing $\boldsymbol{\theta'}$, involves four steps:

1. computation of $\boldsymbol{\delta}$, the estimated distribution of the granulation of $\Theta \cap M$,
2. computation of $\boldsymbol{\gamma}$, the estimated distribution of the granulation of $\Theta \cup M$,
3. computation of π the estimated possibility of M to be coherent with Θ,
4. computation of $\boldsymbol{\theta}'$ as a function of $\boldsymbol{\delta}$, $\boldsymbol{\gamma}$, π and λ.

Formally, the values of the distributions are given as follows:

1. $\forall k \in \Omega$, $\delta_k = \min(\theta_k, \eta_k)$,
2. $\forall k \in \Omega$, $\gamma_k = \max(\theta_k, \eta_k)$,
3. $\pi = Sup_{i,j \in \Omega}(\min(\theta_i, \eta_j, \varpi_{i,j}))$,
4. $\forall k \in \Omega$, $\theta'_k = \lambda.\theta_k + (1-\lambda).(\min(\pi, \delta_k) + \min(1-\pi, \gamma_k).)$

where $\varpi_{i,j} = Sup_x \min\left(\mu_{A_i}(x), \mu_{A_j}(x)\right)$.

In practice, since each set A_i intersects only its two neighbors, we have:

$$\varpi_{i,j} = \begin{cases} 1, \text{ if } i = j, \\ \frac{1}{2}, \text{ if } |i-j| = 1, \\ 0, \text{ otherwise.} \end{cases}$$

2.4 Logical induction

In Section 2.2 we presented the use of the GF to estimate a variable that is measured directly, i.e. Θ, the estimate at the current instant, is a linear function of the measurement M and the estimate of Θ at the previous instant. However, there are situations where the relationship between the current measurement M, the previous estimate Θ and a variable ψ to be estimated is not linear.

The use of the GF in this case simply uses the extension principle to move from the space of the measurements to the space of the variable to be estimated. Let Ψ be the subset of possible current values of ψ.

Let $\{A_i\}_{i=1\ldots n}$ be the partition used for granulating the information about the set Θ and $\{B_i\}_{i=1\ldots p}$ be the partition used for granulating the information about the set Ψ. Granulation of Ψ on $\{B_i\}_{i=1\ldots p}$ provides the vector $\boldsymbol{\psi} = \{\psi_i\}_{i=1\ldots p}$.

Let us suppose that the non-linear relation between ψ, θ and m is on the form of $\psi = f(\theta, m)$. From a crisp point of view, we can write that $\Psi = \{\psi = f(\theta, m) \;/\; \theta \in \Theta, m \in M\}$. Now, taking into account the fact that the information is granularized, estimating Ψ consists in estimating $\boldsymbol{\psi}$ based on $\boldsymbol{\theta}$ and M_k by using the extension principle. We have:

$$\begin{aligned} \forall k \in \{1, \ldots, p\}, \psi_k &= Sup_x \min\left(\mu_{B_k}(x), \mu_\Psi(x)\right), \\ &= Sup_{x,y} \min\left(\mu_{B_k}(f(x,y)), \mu_\Theta(x), \mu_M(y)\right), \\ &\approx Sup_x \min\left(\mu_{B_k}(x), \mu_\Gamma(x)\right), \end{aligned} \tag{2}$$

with $\Gamma(z) = Sup_{x,y} \min\left(\mu_\Theta(x), \mu_M(y) \;/\; z = f(x,y)\right)$.

Practical computation In the case we're interested in here, we have $f(\theta, m) = \arccos(\min(\frac{\theta}{m}, 1))$ (see the introductory section). Let suppose $M = [\underline{m}, \overline{m}]$, and a fuzzy partition $\{B_i\}_{i=1\ldots p}$ on $[0, \pi]$. Lets consider the function $\zeta : \mathbb{R} \mapsto [0, \pi]$ such that $\zeta(x) = \arccos(\min(x, 1))$. Then estimating $\boldsymbol{\psi}$ can be achieved in three steps:

1. for each $i = 1, \ldots, n$, compute the set $\Gamma_i = ⓒ(M \oslash A_i)$, where $\oslash$ is the fuzzy extension of division, and ⓒ the fuzzy extension of ζ by using the L-R representation [3]. M being strictly positive, we have $[\zeta(a_i/\underline{m}), \zeta(a_i/\overline{m})]$ is the core of Γ_i and $[\zeta((a_i + \Delta_a)/\underline{m}), \zeta((a_i - \Delta_a)/\overline{m})]$ is the support of Γ_i,
2. for each $k = 1, \ldots, p$ and each $i = 1, \ldots, n$, compute $\varpi_{k,i} = Sup_x \min(\mu_{B_k}(x), \mu_{\Gamma_i}(x))$ which can be done easily considering that B_k is a triangular number and Γ_i a trapezoidal interval,
3. for each $k = 1, \ldots, p$, compute $\psi_k = Sup_{i=1}^n \min(\theta_i, \varpi_{k,i})$.

Finally, note that this procedure always provides a positive angle. Deciding whether the rotation is positive or negative is achieved by considering the sign of the y translation. If the y translation is positive, then the rotation is positive and vice versa.

2.5 Defuzzification

Although the information given by the granulation on the partition used is rich in information, for (classical) robot control, it is important to reverse the fuzzification process to obtain the most coherent value of the magnitude to be estimated. To this end, several defuzzification processes can be used. Let $\{\theta_i\}_{i=1\ldots n}$ be the distribution to be deffuzzified. Let $\{a_i\}_{i=1\ldots n}$ be the cores of the fuzzy subsets $\{A_i\}_{i=1\ldots n}$ (see Figure 4).

Classical defuzzification The most common way to achieve this defuzzification is to use a weighted sum:

$$\hat{\theta} = \alpha^{-1}. \sum_{i=1}^{n} \theta_i . a_i, \tag{3}$$

with $\alpha = \sum_{i=1}^n \theta_i$. This approach considers the granulated values as expressing the probability of $\theta = a_i$. The purpose of the α factor is to normalize the distribution.

Imprecise defuzzification This method considers the granulated values as expressing the possibility of $\theta = a_i$. In that case, no precise value of $\hat{\theta}$ can be provided, but instead the interval $[\underline{\theta}, \overline{\theta}]$ of possible values of θ [7]:

$$\overline{\theta} = \sum_{i=1}^{n} a_{(i)} \left(\Pi_\pi(\{(i) \ldots (n)\} - \Pi_\pi(\{(i+1) \ldots (n)\}\right), \tag{4}$$

$$\underline{\theta} = \sum_{i=1}^{n} a_{(i)} \left(N_\pi(\{(i) \ldots (n)\} - N_\pi(\{(i+1) \ldots (n)\}\right), \tag{5}$$

with $\forall i = 1 \ldots n$, $\pi_i = \alpha^{-1}.\theta_i$, $\alpha = \max_{i=1}^{n} \theta_i$, $(.)$ being the permutation that sorts the θ_i in ascending order ($\theta_1 \leq \cdots \leq \theta_n$) and for all substet $T \subseteq \{1, \ldots, n\}$, $\Pi_\pi(T) = \max_{i \in T} \pi_i$, $N_\pi(T) = 1 - \max_{i \notin T} \pi_i$. By convention $\{n+1, n\} = \varnothing$. In that case, we use as the defuzzified value, the center of the interval $[\underline{\theta}, \overline{\theta}]$.

Possibility to probability transform based precise defuzzification This method also considers the granulated values as expressing the possibility of $\theta = a_i$, but proposes to use the possibility to probability transform to achieve this defuzzification. In that case, the method is very close to that of Equation (3):

$$\hat{\theta} = \sum_{i=1}^{n} \rho_i.a_i, \tag{6}$$

with $\forall i \in \{1, \ldots, n\}$, $\rho_{(i)} = \alpha^{-1} \sum_{j=i}^{n} \frac{1}{(j)}(\theta_{(j-1)} - \theta_{(j)})$, $(.)$ being the permutation sorting the vector $\boldsymbol{\theta}$ in ascending order and $\alpha = \max_{i=1}^{n} \theta_i$, and $\theta_{(0)} = 0$. Note, however, that since the a_i's are uniformly distributed, the value given by this defuzzification is generally very close to the center of the interval given by the imprecise defuzzification. In contrast to imprecise defuzzification, we'll be referring to it as "precise defuzzification" in the remainder of this article.

3 Experiment on visual servoing

In this section, we explain the setup of our experiment and provide some results and comparison with the classical Kalman Filter (KF) based approach. All the experiments are carried out using simulations, in order to control all the parameters managing the robot's movement and to have a ground truth.

Fig. 5. Simulating the robot and the glue bead.

3.1 Setup

The aim of this work is to inspect the positioning of the glue bead bonding the windscreen to the vehicle's metal frame. To carry out this control, the far-infrared wave sensor is mounted on the end of a 6-axis robot – see Figure (5). The measurement is collected in a vector of 120 values, each value corresponding to a reflection measurement along a 60 mm line. As explained in the introduction, the aim is to keep the orientation of the sensor perpendicular to the axis of the bead, while keeping the center of the bead at the center of the measurement line.

To ensure consistent measurement, the sensor must be held perpendicular to the surface to be measured, at a distance that ensures the electromagnetic beam is focused at the bead. To this end, the roll and pitch angles of the robot's end effector are controlled via the measurements of a stereoscopic sensor (Intel RealSense $D405$). Similarly, the sensor's distance from the windshield surface is controlled by a laser rangefinder.

3.2 Visual servoing

Referring to Figure (1), the purpose of the visual servo system is to control the y-axis displacement of the robot's end device as well as its yaw orientation. Displacement along the x-axis is regular and independent of this servo-control.

To achieve this, at each sampling period the reflectance measurement delivered by the sensor is analyzed to estimate the position of the bead relative to the sensor, as well as the width of the bead. These two estimates are both uncertain and imprecise, as explained in the introduction. Imprecise because the measurement is sampled (position and width are estimated to within one or two pixels). Uncertain because, as can be seen in Figure (2), deducing width and position from the measurement line is subject to random fluctuations.

The y-shift required to keep the bead at the center of the linear image is deduced from the position of the bead center in the measurement line. From the comparison between the estimated width of the bead and its measurement at the sampling time, we deduce the yaw change in orientation required to keep the sensor perpendicular to the main direction of the bead.

3.3 Kaman filtering approach

To filter the measurements with a Kalman filter, taking into account the slow evolution of the underlying variables, we use a first-order model of the form:

$$\begin{cases} \begin{bmatrix} x_{k+1} \\ \dot{x}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} . \begin{bmatrix} x_k \\ \dot{x}_k \end{bmatrix} + \begin{bmatrix} \Delta t^2/2 \\ \Delta t \end{bmatrix} .\epsilon, \\ m_k = \begin{bmatrix} 1 & 0 \end{bmatrix} . \begin{bmatrix} x_k \\ \dot{x}_k \end{bmatrix} + \eta, \end{cases}$$

where x_k is the current state of the value to be estimated, m_k the current measure of this variable, η the measurement noise and ϵ the second derivative of the variable considered as a centered Gaussian random value (noise).

In the Kalman filter equations, two matrices are required which are Q the variance/covariance matrix of the evolution model and R the variance/covariance matrix of the measurement. Q is easily obtained in the form:

$$Q = \begin{bmatrix} \Delta t^2 & \Delta t^3 \\ \Delta t^3 & \Delta t^4 \end{bmatrix} .\sigma_\epsilon^2,$$

where σ_ϵ^2 is the supposed variance of ϵ. This parameter has to be experimentally adjusted. R is the variance of a uniform variable on $[-\alpha, \alpha]$, i.e. $R = \frac{\alpha^2}{3}$.

We use two Kalman filters, one to estimate the position of the center of the bead in the image, the other to estimate the width of the bead. To estimate the angle required to correct the sensor's orientation with respect to the bead, we divide the width estimate by the width measurement, as explained in the introduction – see Figure (3). For the prediction variance, the σ_ϵ^2 value was set at 0.03 for the bead width estimate and 0.1 for the y-deviation estimate y, as these parameters provide the best performance for this approach.

3.4 Guess filtering approach

When using the GF, the procedure is the identical, except that estimates of y-axis position variation and bead width are made using the procedure described in Section 2.3. The parameters used for this experiment are as follows. Width estimation is performed on a partition of 240 triangular subsets distributed over an interval of $[0, 60]$mm. An identical partition is used for the position of the bead center but over an interval of $[-30, 30]$mm. This granulation is in line with the expected measurement imprecision. We use a smoothing factor $\lambda = 0.7$.

For estimating angular variation, we use the procedure described in Section 2.4, using an arbitrary partition of 360 subsets over an interval of $[-\pi, \pi]$.

For defuzzification, we experimented the 3 methods proposed in Section 2.5.

3.5 Comparison

We simulated the movement of a 6-axis robot in which three of the degrees of freedom are controlled by the distance and stereovision sensors (as mentioned previously), while the advance along the x-axis was regular and quasi-static to ensure motion-free measurement of the infrared sensor. y-movement and yaw-angle control make direct use of the information produced by the filters (GF and KF).

We simulated the measurement of a glue bead in accordance with the design of a bead linking the windshield to the frame. Measurements are subjected to Gaussian noise before being sampled. Sampled measurements were then analyzed to extract, for each period, an estimate of the bead width and the position of its center in the sensor reference frame. Imprecise and noisy measurements of bead width and position were filtered out by each filter. This simulation does not fault the Kalman filter. This experiment simply aims at showing that, under nominal conditions, the two approaches give comparable results.

In the case of KF the angle was obtained by calculating the $\cos^{-1}$ of the ratio of the estimated width to the measured width, and decide whether the angle is positive or negative based on the estimated value of the y-deviation.

In the case of GF, the orientation of the bead was calculated according to the procedure described in Section 2.4. Due to the imprecision of the measurement, and its representation by granulation, the fact that the deviation along y is positive or negative is also imprecise information. We therefore used an imprecise defuzzification of the bead position delivering an interval $[\underline{y}, \overline{y}]$ – see Section 2.5. If $0 \leq \overline{y}$ then the distribution is made on the partition considering the angle to be negative. If $0 \geq \underline{y}$ then the distribution is made on the partition considering the angle to be positive. This can naturally lead to a symmetrical distribution of angles if $0 \in [\underline{y}, \overline{y}]$.

As a first result, we found that estimation using possibility to probability transform based defuzzification always gives better results than that using classical defuzzification. In addition, we found that this precise estimate yields values almost identical to those given by the center of the interval given by the imprecise defuzzification. For this reason, we report only the results obtained by precise defuzzification.

Results of estimation errors of y-deviation, bead orientation and width are reported in Table 1 in terms of bias, absolute error and maximum error.

It can be seen that the two filtering approaches give equivalent results for y-deviation, yaw angle and bead width. The only notable difference is that the Kalman approach to yaw angle estimation is slightly biased, as can be seen in Figure (6) .

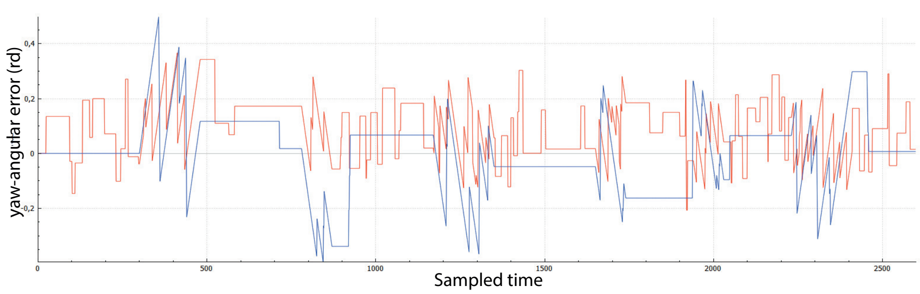

Fig. 6. KF (red) and GF (blue) yaw-angle estimation error .

	y-deviation (mm)		yaw-deviation (rd)		bead width (mm)	
	KF	GF	KF	GF	KF	GF
Mean error (bias)	-0.04	0.005	0.09	-0.002	-0.56	-0.31
Absolute error	0.08	0.10	0.11	0.10	0.58	0.59
Maximal error	0.50	0.58	0.36	0.49	1.40	5.36

Table 1. Error in estimating y-position, yaw angle and bead width.

4 Conclusion

In this article, we have demonstrated that it is possible to use a Guess filter approach instead of a Kalman filter to control a robot using data from a far-infrared sensor. To enable this servo-control based on the analysis of one-dimensional information, we have extended the technique described in [5] to take into account the fact that the data to be estimated is not directly measured. We have carried out a simulated experiment showing that, under normal conditions, GF gives results that are perfectly comparable with those of KF. In future work, we intend to implement a real experiment that we hope will demonstrate the qualities of the GF, which distinguishes the temporal filtering aspect from that of maintaining consistency between estimation and measurement.

References

1. D.Dubois, Prade, H.: Rough fuzzy sets and fuzzy rough sets. International Journal of General Systems **17**, 191–200 (1990)
2. Destercke, S., Dubois, D., Chojnacki, E.: Possibilistic information fusion using maximal coherent subsets. IEEE Transactions on Fuzzy Systems - TFS **17**, 1–6 (08 2007)
3. Oussalah, M., De Schutter, J.: Approximated fuzzy lr computation. Information Sciences **153**, 155–175 (2003)
4. Pawlak, Z.: Rough sets. International Journal of Computer & Information Sciences **11**(8), 341–356 (1982)
5. Strauss, O.: Filtering and fusing compass and gyrometer data using guess filter. In: Proceedings of 6th International Fuzzy Systems Conference. vol. 3, pp. 1593–1599 vol.3 (1997). https://doi.org/10.1109/FUZZY.1997.619779
6. Strauss, O.: Quasi-continuous histograms. Fuzzy Sets and Systems **160**(17), 2442–2465 (2009), theme: Learning
7. Strauss, O., Rico, A., Hmidy, Y.: Macsum: A new interval-valued linear operator. International Journal of Approximate Reasoning **145**, 121–138 (2022)