FAULT-TOLERANT WELD LINE DETECTION BASED ON DISTANCE AND VISUAL INFORMATION FUSION

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Abstract: Quality control, cost reduction and above all, human and environmental safety are great reasons that stimulate the investments in technologies like automatic inspection. The automatic inspection of weld lines in storage tanks is of special interest, due to the fact that such tanks are currently used to store harmful products. For a reliable inspection it is necessary to accurately detect the weld line position. In this paper the development of a system to perform weld line detection in storage tanks is proposed. Two redundant systems, based on different physical principles, distance and visual information, are implemented and tested. Such systems make use of a fault-tolerant estimation process based on the $\alpha$-$\beta$ filter. Finally, the outputs of the two redundant systems are fused, aiming at to increase the confidence and performance of the system.

Keywords: Weld line detection, $\alpha$-$\beta$ filter, fault-tolerant, information fusion.

1. INTRODUCTION

Quality control, cost reduction and above all, human and environmental safety are great reasons that stimulate the investments in technologies like automatic inspection. The automatic inspection of weld lines in storage tanks is of special interest, due to the fact that such tanks are currently used to store harmful products. Such tanks should be frequently inspected to assure the integrity of their physical structure.

In this context, robotic inspection systems became a reality in such sector, allowing a more confident inspection, through minimizing the human error probability, and carrying out such process faster and at lower costs.

The development of methods to enable inspection of such tanks at lower costs, with greater safety and in a shorter time than present methods has been sought [1].

Taking into account this necessity of the industrial sector, in this work is proposed the development; implementation and testing of a system to perform the weld line detection for automatic inspection of storage tanks.

A way to perform the non-destructive inspection of weld lines is based on the emission of high-frequency ultrasonic waves, propagating in solid environments. Such ultrasonic waves are emitted in several angles through the reservoir structure, propagating around it. When there are air bubbles inside the weld line, the ultrasonic waves are reflected, allowing the fault detection [2][3].

This kind of process is already in use, but its confidence is affected when it is not possible to guarantee that the inspection sensor is positioned at the center of the weld line.

At this point it is important to state that the detection of faults inside of the weld line structure is beyond the scope of this work. It is focused only in the reliable detection of the weld line position, which is important information to guide the positioning of the inspection sensor used to detect the faults inside the structure of the weld line.

As sensory information is incomplete and imprecise, due to noise, limited sensor resolution and imprecise conversion of its physical measurements, a unique sensor will not be able to deal with all kind of situations that it might be exposed during its operation.

Richardson and Marsh [4] presented a mathematical proof that the inclusion of new sensors in a sensory system may improve, but will never deteriorate its performance, in other words, the result obtained fusing data from several sensors are more reliable than the data from each sensor.

Accordingly to [5], the use of fusion of information provided by different sensors may produce several benefits, like uncertainty and errors reduction and increasing spatial and time coverage.

To accomplish the task of weld line detection with a higher confidence level, two redundant systems, based on different physical principles, in this case distance and visual information, are implemented and tested. Such systems make use of a fault-tolerant estimation process [6][7] based on the $\alpha$-$\beta$ filter [8]. In the context of this work, weld line detection means to measure the orientation and the position of the weld line with respect to the inspection sensor.

Finally, the outputs of such redundant systems should be fused, aiming at to increase the confidence and performance of the system [9].

In [10], a fault-tolerant system to perform weld line detection based on distance and visual information was developed. However, the distance and visual information were fused using a simple and sub-optimal estimator presented in [9]. So, in order to increase the robustness and reliability of the entire system, the search for a more elaborated, and maybe optimal, fusion approach was proposed as a future work.

In this sense, the approach presented in [10] is extended in this work by the proposition of an Information Filter (an optimal estimator, in the sense that it minimizes the mean squared error) [20] to perform the visual and distance information fusion step. This extension should contribute to improve system’s robustness and reliability.

2. THE PROPOSED APPROACH

In this section the proposed approach will be explained in details. First, in Subsection 2.1 the approach based on distance information is presented. Then, the visual
information based approach is introduced. In the sequence the fault-tolerant estimation process is explained, and the section ends with the presentation of the data fusion process used in this work.

2.1. Distance Information Based Approach

As can be seen in Fig. 1, the weld lines found in storage tanks present a bigger thickness than that of the plates that they are joining. This weld layer that exceeds the metallic surface level is called reinforcement layer, and it is about 5 mm of height. So, using distance sensors it is possible to accurately detect the weld line position.

![Weld line and metallic plate profile.](image1)

In [11] the use of an array of infrared distance sensors, as shown in Fig. 2, was proposed.

![Sensor arrangement to perform weld line detection.](image2)

The resolution of the systems used to perform weld line detection based on distance sensors is low, due to the size of them [12]. As a way to increase the resolution of the system, and consequently, its precision and exactness, the Sinc Interpolation will be used. Using Sinc Interpolation, and under ideal circumstances, it is possible to entirely recover a signal from its samples [13],[14].

Accordingly with the Nyquist’s Sample Theorem, samples of a band-limited signal, gathered at a fixed and known sampling period, are enough to allow a complete recovery of the signal, if the sampling frequency, \( \Omega_s \), is at least two times greater than the signal bandwidth, \( \Omega_N \).

The sampled signal, \( x_s(t) \), may be represented by:

\[
x_s(t) = \sum_{n} x[n] \delta(t - nT)
\]

where \( x[n] \) stands for the sequence of samples, \( n \) is the sample number at the sequence, \( \delta \) is the impulse function, and \( T \) is the sampling period.

If the Nyquist’s sample theorem holds, and the sampling period is known, the signal may be recovered from its samples. In order to do this, the sequence of samples must be passed through a continuous-time low-pass filter with a cutoff frequency, \( \Omega_c \), between \( \Omega_s \) e \( \Omega_s - \Omega_N \), which was conveniently selected as \( \Omega_c = \Omega_s/2 = \pi/T \) [13],[14].

In the time domain this process is equivalent to:

\[
x(t) = \sum_{n} x[n] \text{sinc} \left(t - nT/T\right)
\]

where \( x(t) \) is the recovered signal.

With the recovered signal it is possible to detect its peak, which should correspond to the center of the weld line.

To detect the weld line position and orientation deviations (\( \epsilon \) and \( \phi \)) with respect to the position of the inspection sensor, two arrays of infrared distance sensors are necessary. They should be positioned as shown in Fig. 3. Knowing the weld line center positions \( \epsilon_f \) and \( \epsilon_r \), calculated using the front and rear arrays respectively, and the distance separating both arrays (\( d \)), it is possible to know the weld line orientation using

\[
\epsilon = \frac{\epsilon_f + \epsilon_r}{2}
\]

\[
\phi = \tan^{-1} \left[ \frac{\epsilon_f - \epsilon_r}{d} \right]
\]

2.2. Visual Information Based Approach

The visual information based approach is presented in the sequence. First, a robust texture based segmentation method is used to identify the image pixels which are part of the weld line. Then a modified Hough transform, first introduced in [15] is used to find the coordinates (\( \rho \) and \( \theta \)) which best represents the weld line that appears in the image.

2.2.1. The Segmentation Method

The segmentation method proposed is based on texture information acquired through the second central moment [16]. The entropy maximization of a one-dimensional histogram is used, but, as proposed in [15], the histogram is made from a vector representing a sampling of standard deviations of non-overlapping regions, which cover the entire original image.

As shown in [15], this segmentation method does not need the histogram equalization step, and the choice of the threshold is optimal in sense of entropy maximization as showed by Kapur [14].

2.2.2. The Modified Hough Transform

The Hough Transform is a classical method to detect curves in binary images, widely used and studied by several authors. An overview about this subject is found in [18].

The weld line may be considered as a straight line, which can be considered in several ways. The most suitable one is the parametric equation of the straight line:

\[
\rho = x \cos \theta + y \sin \theta
\]

The input to the Hough Transform is a binary image, obtained from the segmentation step.
Different from the classical Hough Transform, in which the most voted set of parameters \((\rho, \theta)\) is chosen as the ones whose better represents the weld line, the modification inserted by Molina [15], consists in to select a set of them.

In this approach, each vector \(\theta_i\) (composed by each column of the accumulators matrix), independently, is submitted to a fitting process with a window function, which identify the lines found in the image that do not correspond to the weld line, and, thus, reduces the sensitivity to biased noises.

A valid observation window is determined to each vector \(\theta\). Then, the search for the window with the lowest variance in the related values of \(\rho\) is made, with the objective to find a similar voting for different values of \(\rho\) in the same \(\theta_i\). The value of \(\theta\) with the lowest variance in the observation window and that, at the same time, has a minimum amplitude of considered voting, is the \(\theta\) that better represents the weld line in the image, and the corresponding value of \(\rho\) is the average point of the observation window that got the lowest variance in the previously described analysis [15].

Considering that origin is the inferior left corner of the image, the \(\varepsilon\) and \(\varphi\) parameters of interest may be calculated from \(\rho\) and \(\theta\) using equations (6) and (7):

\[
\varepsilon = \frac{\rho - w \cos \theta}{2} \tag{6}
\]

\[
\varphi = \begin{cases} 
\frac{\pi}{2} + \theta, & \text{if } \theta > 0 \\
\frac{\pi}{2} - \theta, & \text{if } \theta < 0 
\end{cases} \tag{7}
\]

where \(h\) is the image height and \(w\) is the image width.

### 2.3. The Fault-Tolerant Estimation Process

The two approaches developed to perform the detection of weld lines are able to calculate the two parameters of interest. But, in both cases, under certain circumstances, may be impossible to detect the weld line. In the case of the distance information approach, for example, sometimes the reinforcement layer is not continuous. So, the distance information approach will fail. However, the parameters of interest could be measured even in this situation if some kind of data estimation process is used.

Similar considerations can be made in the case of the vision information based approach. A fault, in this case, may occur due to illuminations problems or the dirt accumulation over the tank surface.

In order to increase the confidence of the obtained parameters, the use of an estimation process based on the \(\alpha-\beta\) filter [8] is proposed to be used as a post-processing step to both of the approaches previously presented.

The \(\alpha-\beta\) filter, with proper \(\alpha-\beta\) parameters, is the optimal solution of the Kalman filtering process for the stationary target tracking problem in steady-state [8]. The \(\alpha-\beta\) filter may be used if the following parameters may be considered as constants [8]: sampling period; measurement noise variance; acceleration.

Consider the relative motion between the inspection sensor and the weld line center as a target, and suppose that such target has a linear motion which can be described by the following equations:

\[
x(k + 1) = x(k) + T_0 v(k) + \frac{1}{2} T_0^2 w(k) \tag{8}
\]

\[
v(k + 1) = v(k) + T_0 w(k) \tag{9}
\]

where \(T_0\) is the sampling period and \(w(k)\) is the unknown acceleration of the target.

The target position is observable through measurements performed by the infrared arrays or obtained using the image processing scheme presented in Subsection 2.2. Such measurements may be modeled by the following equation:

\[
z(k) = x(k) + n(k) \tag{10}
\]

where \(n(k)\) is the measurement noise.

Considering the specific case of this work, the \(\alpha-\beta\) filter equations are presented in the sequence:

**Linear motion equations:**

\[
\begin{align*}
\rho(k + 1) &= \rho(k) + T_0 v(k) \\
\theta(k + 1) &= \theta(k) + T_0 \omega(k)
\end{align*} \tag{11}
\]

**Measurement:**

\[
z(k) = \rho(k) + \theta(k) + n(k) \tag{12}
\]

**Prediction:**

\[
\begin{align*}
\hat{\rho}(k | k + 1) &= \hat{\rho}(k | k) + T_0 \dot{v}(k) \\
\hat{\theta}(k | k + 1) &= \hat{\theta}(k | k) + T_0 \dot{\omega}(k)
\end{align*} \tag{13}
\]

**Estimation:**

\[
\begin{align*}
\hat{\rho}(k + 1 | k + 1) &= \hat{\rho}(k + 1 | k) + \alpha \left[ \rho(k + 1) - \hat{\rho}(k + 1 | k) \right] \\
\hat{\theta}(k + 1 | k + 1) &= \hat{\theta}(k + 1 | k) + \alpha \left[ \theta(k + 1) - \hat{\theta}(k + 1 | k) \right] \\
\hat{v}(k + 1 | k + 1) &= \hat{v}(k + 1 | k) + \beta \left[ v(k + 1) - \hat{v}(k + 1 | k) \right] \\
\hat{\omega}(k + 1 | k + 1) &= \hat{\omega}(k + 1 | k) + \beta \left[ \omega(k + 1) - \hat{\omega}(k + 1 | k) \right]
\end{align*} \tag{14}
\]

Accordingly with [8], the tracking index \(\Lambda\) is given by:

\[
\Lambda = \beta^2 \frac{1}{1 - \alpha} \tag{16}
\]

The relationship between the optimal \(\alpha-\beta\) parameters is obtained by:

\[
\beta = 2(2 - \alpha) - 4\sqrt{1 - \alpha} \tag{17}
\]

Combining (16) and (17) the optimal values of the \(\alpha-\beta\) parameters may be explicitly obtained in terms of \(\Lambda\), by:

\[
\alpha = \frac{\Lambda^2 + 8\Lambda - (\Lambda + 4)\sqrt{\Lambda^2 + 8\Lambda}}{8} \tag{18}
\]

\[
\beta = \frac{\Lambda^2 + 4\Lambda - \sqrt{\Lambda^2 + 8\Lambda}}{4} \tag{19}
\]

The proposed fault-tolerant estimation process is presented in Fig. 4 in the form of a block diagram. Some special attention must be dedicated to the vector \(r(k)\), known as the residual vector. The residual is defined as the difference between the output of the system and the output estimated using the model of the system [6]. In this case, the residual vector is given by:

\[
r(k + 1) = [\rho(k + 1) - \hat{\rho}(k + 1 | k)] \tag{20}
\]

![Fig. 4. Fault-tolerant estimation process.](image)
When the sensory system fails in the measurement of the parameters \( \varepsilon \) and \( \varphi \), the residual value grows. If a threshold value is crossed, a fault is detected. This threshold comparison is performed by the “Decision Making” block. When a fault is detected, the “Decision Making” block signalizes the “Estimation” block that the available observation vector is not reliable. In this case, the estimation phase of the \( \alpha-\beta \) Filter is not executed, and the prediction obtained in the output of the prediction phase is considered as the output vector of parameters [7][19].

### 2.4. Data Fusion

The parameters obtained by each approach after the fault-tolerant estimation process should be fused to increase, even more, the confidence of the weld line detection system [4][5].

In [20] the theory of the information filter, used in this work to perform the data fusion, is presented. In algebraic terms, the information filter is equivalent to the Kalman Filter [20]. However, the information filter is easier to initialize. When using a Kalman Filter, a previous knowledge of the system is necessary in order to obtain the initial estimate and to initialize the covariance error matrix \( P' \) [9], [21]. By its turn, the information filter can be initialized simply making the state information vector \( y' \) equal to zero and the information matrix \( Y' \) equal to a small, but non-zero value (to allow its inversion). This is due to the fact that when starting the execution of the information filter there is no information available. Actually, it starts increasing along the time. In other words, the information filter is more robust than the Kalman filter when regarding the initialization [20], [22]. Following, the information filter equations are presented [20].

Suppose a system whose model is given by

\[
x(k) = F(k)x(k-1) + B(k-1)u(k-1) + w(k)
\]

(21)

\[
z(k) = H(k)x(k) + v(k)
\]

(22)

where \( F \) is the state transition matrix, \( x(k) \) is the \( nx1 \) state vector, \( z(k) \) is the \( nx1 \) observation vector in the instant \( k \), \( B(k-1) \) is the control matrix and \( u(k-1) \) is the action of control. By its turn, \( H \) is the observation matrix, which relates the state to the observation, \( w(k) \sim N(0,Q(k)) \) is the noise associated to the system and \( v(k) \sim N(0,R(k)) \) is the noise associated to the observation, both modeled as white, uncorrelated, zero-mean sequences containing the covariance of the process noise and the covariance of the observation noise, respectively.

Information matrix:

\[
Y(k) = P'(k)
\]

(23)

State information vector:

\[
\hat{y}(k) = P'(k)\hat{x}(k) - Y(k)\hat{x}(k)
\]

(24)

Prediction:

\[
\hat{y}(k) = L(k)\hat{y}(k-1)
\]

(25)

\[
Y(k) = \left[ F(k)Y^{-1}(k-1)F^T(k) + Q(k) \right]^{-1}
\]

(26)

### 3. RESULTS

The positioning of the sensors used to perform the weld line detection and inspection processes is shown in Fig. 3. Several laboratorial experiments were performed to verify the performance of the system and some of the obtained results are shown in next subsections.

#### 3.1. Distance Information Based Approach Results

In the case of the distance information based approach the initial tests consisted in detect the center of the weld line, which should correspond to the peak of the profile of its reinforcement layer. A sample of the obtained results is presented in Fig. 5. The Sinc interpolator results from the fifteen samples of the weld line profile acquired by the front and rear arrays of infrared sensors, are presented.

Using results (like those presented in Fig. 5) provided by the front and rear arrays of infrared sensors (Fig.3), and equations (3) and (4), the parameters of interest, \( \varepsilon \) and \( \varphi \), were obtained. The results of one of the several experiments performed under laboratory conditions are shown in Fig. 6. In the considered experiment a sine movement was made with the sensory platform with respect to the weld line.

#### 3.2. Visual Information Based Approach Results

In the case of the visual information approach, several experiments were carried out based on images obtained from weld lines of storage tanks using a VGA resolution digital camera. The images were processed using the method previously mentioned in Subsection 2.2, and a detailed description of it may be found in [15].
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3.3. Fault-Tolerant Estimation Process Results

The result of the application of a fault-tolerant estimation process to the data obtained using the distance information based approach is shown in Fig. 9, while similar results considering data provided by the visual information based approach are shown in Fig. 10.

As can be noticed, in both cases, the fault-tolerant estimation process was able to smooth the curves and to avoid the failures occurred during the experiment.

3.4. Data Fusion Results

The results of the data fusion process between the data provided by the two available approaches are presented in Fig. 11. The obtained data after the fusion process are the most reliable considering the available data.
The fusion process produced the most reliable data considering the available information. Using data fusion the system is able to handle situations in which one of the available sensory systems stops working due to some kind of failure. Such feature is very important when considering the need to frequently inspect tanks that may be used to store harmful products.

In this paper, as an optimal estimator was used to perform the data fusion process, namely the information filter, the system performance is improved, resulting in a more robust and reliable approach than the one previously presented in [10].

As a future work further experiments, this time performed in real industrial installations, are proposed. Also, the system should be mounted over a mobile platform now under construction by another research group. Then, more experiments will be necessary to validate the complete system working under real operational conditions.

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4. CONCLUSIONS

As can be noticed due to the results presented in the previous section, each one of the two proposed approaches works well and can be used to perform weld line detection. Also, the fault-tolerant estimation process, carried out based on the α-β filter, was able to avoid the failures occurred in the experiment, and to significantly reduce noise.
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