FAULT-TOLERANT WELD LINE DETECTION FOR AUTOMATIC INSPECTION OF STORAGE TANKS BASED ON VISUAL INFORMATION AND ALFA-BETA FILTER

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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 such as 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. The system based on visual information, are implemented and tested. Such system makes use of a fault-tolerant estimation process based on the α-β filter and a data-based fault detection method, proposed in this paper.

Keywords— Weld Line Detection, Image Processing, α-β Filter, Fault-Tolerant Estimation.

Resumo— Controle de qualidade, redução de custos e acima de tudo segurança são interesses que estimulam os investimentos em tecnologia, como a utilizada nos processos de inspeções automatizada. A inspeção automatizada de linhas de solda em tanques de armazenamento é de especial interesse devido ao fato de tais tanques serem normalmente utilizados no armazenamento de produtos nocivos ao homem. Para garantir a eficácia da inspeção, é necessário detectar corretamente a posição da linha de solda. Neste artigo é proposto o desenvolvimento de um sistema para realizar a detecção da linha de solda. O sistema baseado em imagens é implementado e testado. Tal sistema se utiliza de um processo de estimação tolerante a falhas baseado no filtro α-β e em um método de detecção de falhas baseado em dados, proposto nesse artigo.

Palavras-chave— Detecção de linha de solda, processamento de imagens, filtro α-β, estimação tolerante a falhas

1 Introduction

Quality control, cost reduction and above all, human and environmental safety are great reasons that stimulate investments in technologies such as 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 and should be frequently inspected to guarantee the integrity of their physical structure. In this context, robotic inspection systems has become a reality, allowing more confident inspections, since it minimizes the human error probability, and carries out the inspection task faster and at lower costs (Carvalho et al., 2007).

One of the most reliable ways to perform the non-destructive inspection of weld lines is based on the emission of high-frequency ultrasonic waves that propagate 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, leading to the fault detection (see Li and Liao (1996) and the references therein). It is important to mention that only inspection has been considered in Li and Liao (1996) since the inspection process does not need to follow the weld line automatically. In order for this inspection to be effective, when performed automatically, it is mandatory that the ultrasonic sensor be positioned at the center of the weld line. Thus, prior to actually address the problem of detecting faults inside the weld line structure, it is necessary to find a reliable way to perform the detection of the weld line position with the view to guiding the positioning of the ultrasonic sensor.

The problem of weld line detection on fuel storage tanks using image processing ideas has considered by Molina et al. (2008). The vision system proposed in Molina et al. (2008) has provided the necessary information to keep a set of ultrasonic sensors, used to inspect the weld line, in the necessary position in order to improve the inspection reliability, in spite of sensor (camera) information being imprecise due to noise, limited resolution and imprecise conversion of its physical measurements. However, this method has a physical restriction due to the nature of the camera that requires a quite clear light source to be able to capture good quality images. In addition, the resulting measured position may present some polarized noise due to, among other factors, failure on the illumination system or spots of light that corrupt the image. In this case, the system confidence is not guaranteed, making impossible to carry out the automatic weld inspection process due to the bad positioning of the sensor. Moreover, it is possible to notice a noise measurement associated with the data obtained through the image processing, which also complicates the task.

This paper also deals with the problem of performing weld line detection for automatic inspection of storage tanks. All the restrictions of the method proposed in Molina et al. (2008) have been considered. A fault detection data-based approach is proposed as a solution that minimizes the sensor noise measurement and ensures the operation of the system even in the presence of faults (Pettersson, 2005). The fault-tolerant estimation system proposed here has two main components: (i) an α-β filter (Kalata and Murphy, 1997); (ii) the fault detection database system. Moreover, to achieve the feedback of the control system that makes the correct positioning of the inspection sensor it is also necessary to estimate the linear and angular velocities, which is also made by the proposed system. At this point, it is important to stress that the weld line inspection (*i.e.* detection of faults inside the weld line structure) is beyond the scope of this work. This work is only focused in the weld line detection.

This paper is organized as follow: a description of the measurement method using images and their practical problems are presented in Section 2; the fault-tolerant estimation method is proposed in Section 3, where the results obtained experimentally for this method are also presented; finally, conclusions are drawn in Section 4.

2 Position and orientation estimation using image processing

The visual-based approach proposed by Molina et al. (2008) will be reviewed in the sequel. This method consists of two parts: (i) a robust texture-based segmentation method that is used to identify the image pixels that are part of the weld line; (ii) a modified Hough transform, first introduced in Molina, et al. (2008) is used to find the coordinates ρ and θ which best represents the weld line that appears on image. These parts will be briefly described below.

2.1. The Segmentation Method

The segmentation method is based on texture information acquired through the second central moment (Gonzales et al., 2002). The entropy maximization of a one-dimensional histogram is used, but as proposed by Molina et al. (2008), 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 Molina, et al. (2008), this segmentation method does not need the histogram equalization step, and the choice of the threshold is optimal regarding entropy maximization, as showed by Kapur et al. (1985).

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 (see Kälviäinen et al. (1995) and the references therein).

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

$$\rho = x\cos\theta + y\sin\theta.$$

The input of the Hough transform is a binary image, obtained from the segmentation step (i). The modification carried out by Molina, et al. (2008) in the classical Hough transform, consists in selecting a set of pair of parameters (ρ, θ) that better represents the weld line. In this approach, each vector θ_i (composed of each column of the matrix of accumulators), is, independently, submitted to a fitting process with a window function, which identifies the lines found in the image that do not correspond to the weld line; therefore reducing the sensitivity to biased noises.

A valid observation window is determined for each vector θ. After that, the search for the window with the lowest variance in the related values of ρ is performed with the objective of finding a similar voting for different values of ρ associated with the same θ_i. The value of θ with the lowest variance in the observation window and that, at the same time, has , in the voting that is being performed, the minimum amplitude, is the value of θ that better represents the weld line in the image. The corresponding value of ρ is the average point of the observation window that achieves the lowest variance (Molina, et al., 2008).

The results for a regular image using the method described above are shown in Figure 1. Notice that for the blue point shown on the weld line, the value of θ is acceptable since the straight line in red approximately follows the weld line and the value of ρ is slightly smaller than it should be.

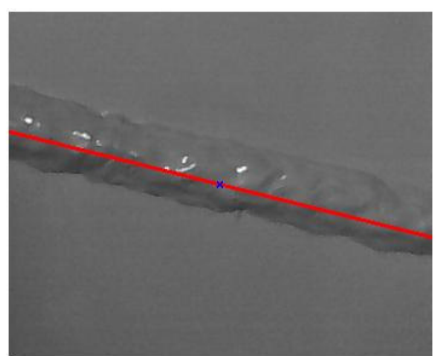

Figure 1. Results from the filet weld detection system applied on a regular image.

The lack of lighting jeopardizes the application of the method, but this drawback can be easily corrected by ensuring the minimum controlled lighting for the system. On the other hand, strong illumination sources in the environment also affect the detection of the weld line, as one can see in Figure 2. These situations can occur at any time and are not predictable, thus characterizing a serious problem for weld line detection.

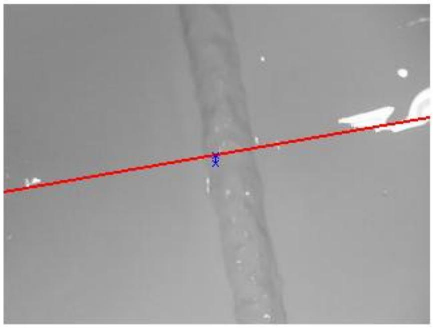

Figure 2. Results from the filet weld detection system applied on a corrupted image.

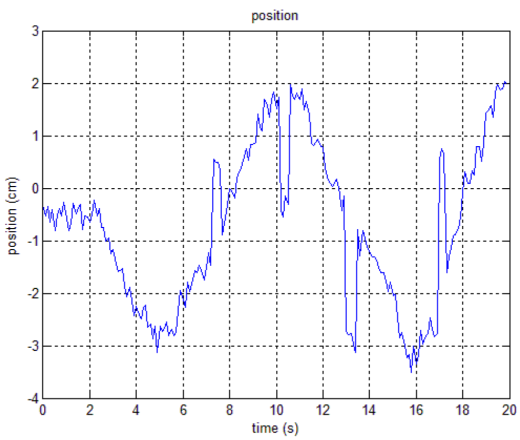

Figure 3. Position obtained directly from the explained approach.

Since the visual-based system proposed in Molina et al. (2008) was meant to be part of a robotic system that performs inspection of weld lines, in order to validate the theoretical results, several tests were carried out in which a robot was moved around in a partially structured environment and the behavior of the position (ρ) and orientation measurements (θ) were observed. The results are shown in Figures 3 and 4. As one can see, a few jumps that correspond to failure in the measurement process (mainly due to illumination problems) can be noticed in the plots. In addition high-frequency noises are also depicted in the plots.

3 Fault-tolerant estimation process

The approach developed by Molina et al. (2008) to perform the weld line detection has been proved effective in the calculation of the two parameters of interest (ρ and θ). However, as explained above, under certain circumstances (e.g. illumination problems and dirt accumulation over the tank surface), it may not be possible to detect the weld line correctly. This characterizes a failure in the weld line detection.

In order to increase the calculated parameter confidence, this paper proposes the use of an estimation process (Gelb et al., 1999) based on the α-β filter (Kalata and Murphy, 1997) as a post-processing step together with a fault detection system. The proposed fault-tolerant estimation process is represented by the block diagram of Figure 5.

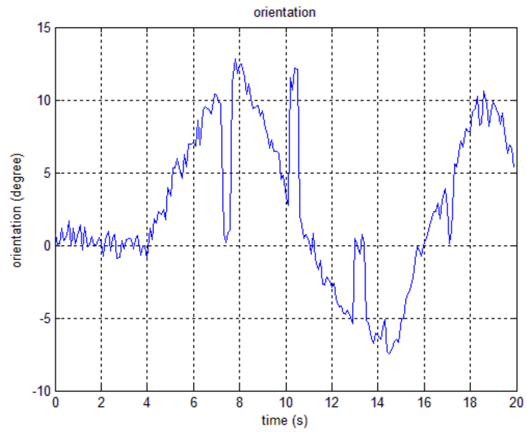

Figure 4. Orientation obtained directly from the explained approach.

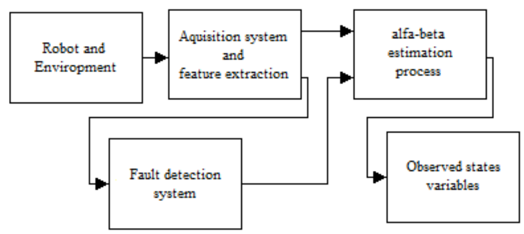

Figure 5. The proposed fault-tolerant estimation process as a block diagram.

3.1 The α-β filter

The α-β filter, with proper α-β parameters, is the optimal solution of the Kalman filtering process (Noriega, 1992) for the stationary target tracking problem in steady-state (Kalata and Murphy, 1997). It may be used when the following parameters may be considered as constant (Kalata and Murphy, 1997): (i) sampling period; (ii) measurement noise variation and; (iii) acceleration.

Consider the relative motion between the inspection sensor and the weld line center as a target, and suppose that such a target has a slow and linear motion. Then the position x(k+1), at the sampling instant k+1, can be obtained as a function of the position x(k), the velocity v(k) and the unknown target acceleration w(k), at the sampling instant k, according to the following equations:

$$x(k+1) = x(k) + T_0 v(k) + \frac{1}{2} T_0^2 \omega(k),$$

$$v(k+1) = v(k) + T_0 \omega(k),$$

where T_0 is the sampling period.

The target position x(k) is observable through measurements z(k) performed by the image processing scheme presented in section 2. Such measurements may be modeled by the following equation:

$$z(k) = x(k) + n(k),$$

where n(k) is the measurement noise.

Considering the specific case of this work, the α-β filter equations are as follows:

1. Linear motion equations:

$$\begin{bmatrix} \rho(k+1) \\ \theta(k+1) \end{bmatrix} = \begin{bmatrix} \rho(k) \\ \theta(k) \end{bmatrix} + T_0 \begin{bmatrix} v(k) \\ \omega(k) \end{bmatrix};$$

2. Measurement:

$$\mathbf{z}(k) = \begin{bmatrix} \rho(k) \\ \theta(k) \end{bmatrix} = \begin{bmatrix} \rho_r(k) \\ \theta_r(k) \end{bmatrix} + n(k)$$

where ρ_r and θ_r are the values of position and orientation without the measurement noise.

3. Prediction:

$$\begin{bmatrix} \hat{\rho}(k+1|k) \\ \hat{\theta}(k+1|k) \end{bmatrix} = \begin{bmatrix} \hat{\rho}(k|k) \\ \hat{\theta}(k|k) \end{bmatrix} + T_0 \begin{bmatrix} \hat{v}(k|k) \\ \hat{\omega}(k|k) \end{bmatrix};$$

4. Estimation:

$$\begin{bmatrix} \hat{\rho}(k+1|k+1) \\ \hat{\theta}(k+1|k+1) \end{bmatrix} = \begin{bmatrix} \hat{\rho}(k+1|k) \\ \hat{\theta}(k+1|k) \end{bmatrix} + \alpha \begin{bmatrix} \rho(k+1) - \hat{\rho}(k+1|k) \\ \theta(k+1) - \hat{\theta}(k+1|k) \end{bmatrix};$$

$$\begin{bmatrix} \hat{v}(k+1|k+1) \\ \hat{\omega}(k+1|k+1) \end{bmatrix} = \begin{bmatrix} \hat{v}(k|k) \\ \hat{\omega}(k|k) \end{bmatrix} + \frac{\beta}{T_0} \begin{bmatrix} \rho(k+1) - \hat{\rho}(k+1|k) \\ \theta(k+1) - \hat{\theta}(k+1|k) \end{bmatrix};$$

According to Kalata and Murphy (1997), the tracking index Λ is given by:

$$\Lambda^2 = \frac{\beta^2}{1-\alpha} \tag{1}$$

The relationship between the optimal α-β parameters is given by:

$$\beta = 2(2-\alpha) - 4\sqrt{1-\alpha} \tag{2}$$

Combining Equations (1) and (2), the optimal values for the α-β parameters may be explicitly written in terms of Λ, as follows:

$$\alpha = \frac{-\left(\Lambda^2 + 8\Lambda - (\Lambda+4)\sqrt{\Lambda^2 + 8\Lambda}\right)}{8} \tag{3}$$

$$\beta = \frac{\Lambda^2 + 4\Lambda - \Lambda\sqrt{\Lambda^2 + 8\Lambda}}{4} \tag{4}$$

Remark 1. Notice in Equations (3) and (4) the depence of α and β on Λ, which has to be assigned by the designer.

3.2 The data-based execution monitoring system

Execution monitoring systems, also known as fault detection and isolation, can be of three different types (Pettersson, 2005; Gertler, 1998):

1. Model-based;
2. Data-based;
3. Knowledge-based.

Model-based systems use a model of the system to compare the system and model responses (see Freire. et al. (2008) and the references therein) to obtain the residual information. In contrast to model-based approach, the data-driven approach does not rely on mathematical models. Instead, the information used for fault detection and isolation is derived directly from input data (see Figure 6). The strength of data-driven approaches is their ability to transform the high-dimensional data into a lower dimension space, in which the important information is captured. The main drawback using this approach is that the performance is highly dependent on the amount and quality of the input data. On the other hand, it is not necessary to use models to process the information, which makes the use of data-based methods particularly simple and interesting. Knowledge-based systems are widely used in many research fields, and represent the methods that combine the model-based and data-based characteristics or that use tools that come from Artificial Intelligence, Pattern Recognition, Neural Networks and others (Gertler, 1998).

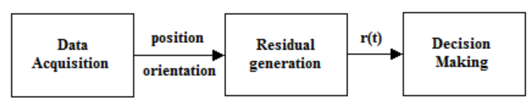

Figure 6. Procedure to determine the occurrence of a fault in the system monitored.

The execution monitoring system proposed in this paper is data-based. The residue generation uses information about the variance of the input data coming from the image processing discussed in section 2. The residue r(k+1) is expressed as:

$$r(k+1) = \Delta\rho + \Delta\theta,$$

where $\Delta\rho = \rho(k+1) - \rho(k)$ and $\Delta\theta = \theta(k+1) - \theta(k)$ are the increment observed to ρ and θ, respectively.

The decision making is usually based on statistical methods (Gertler, 1998). However, in this work a new decision method, based on discrete event system models (Cassandras and Lafortune, 2006) is proposed to determine the occurrence or not of a failure. In order to do so, consider the automaton:

$$G = (X, E, f, \Gamma, x_o, X_m),$$

where:

$$\begin{cases} X = \{0,1,2,3\} \\ E = \{a,b,c\} \\ \Gamma(\mathrm{x}_i) = \mathrm{E}, \mathrm{i} = 1,2,3, \\ x_0 = 0 \\ X_m = X \setminus \{x_0\} = \{1,2,3\} \end{cases}$$

The transition function f to each state can be inferred observing the automaton showed in Figure 7. States 1 is the normal behavior state, states 2 and 1are faulty behavior states associated with positive and negative residue jumps, respectively, and state 3 is a state where the system should be before leaving the faulty behavior. The automaton illustrated also represents the state evolution of the decision making system, here proposed. The events (a, b, c) that control the state transitions have are related to the residual information *r(k)*, as follows:

$$\begin{cases} a = r(k) > 0.5 \\ b = r(k) < -0.5 \\ c = -0.5 \leq r(k) \leq 0.5 \end{cases}$$

The occurrence of any one of these events automatically produces a state transition in G, as shown in Figure 7.

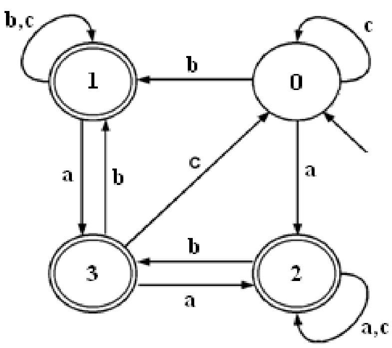

Figure 7. Automaton G, illustrating the state evolution of the decision making system proposed.

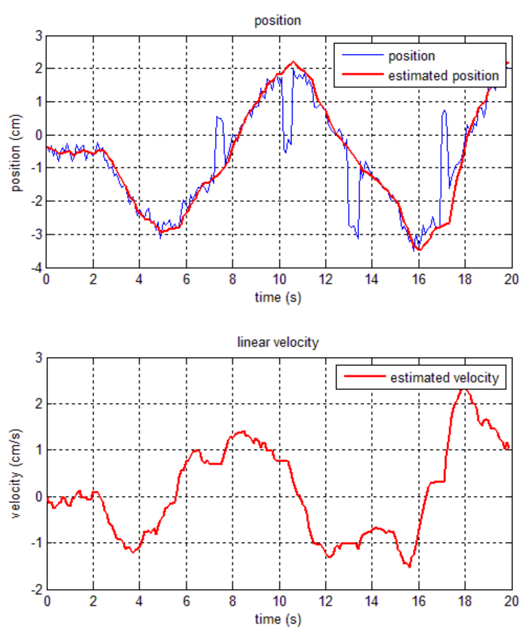

Figure 8. a) Position obtained directly from the explained approach and by the fault-tolerant estimation process. b) Linear velocity estimated by the fault-tolerant estimation process.

The results obtained from the application of the fault-tolerant estimation process to the data obtained using the data provided by the visual information based approach (Figures 3 and 4) are shown in Figures 8 and 9. The residue *r(k)* for this experiment and the automaton output indicating the presence or not of a failure situation are shown in Figure 10.

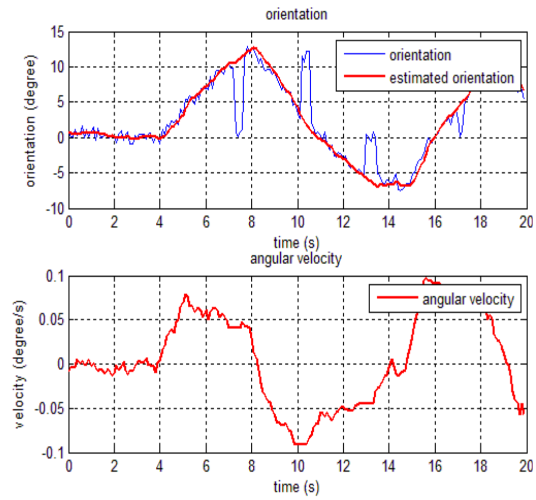

Figure 9. a) Orientation obtained directly from the explained approach and by the fault-tolerant estimation process. b) Angular velocity estimated by the fault-tolerant estimation process.

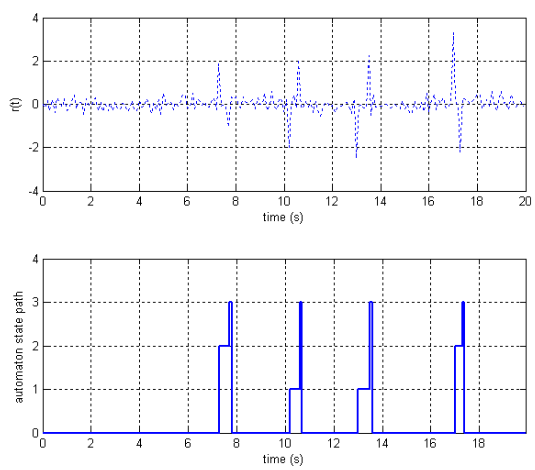

Figure 10. The residual r(t) and the automaton state path showed as the number of the state.

As one can notice, the fault-tolerant estimation process was able to smooth the curves and to avoid the failures occurred during the experiment and to provide a good estimation for the angular and liner velocity of the system that which had not been obtained by the method presents on section 2.

4 Conclusion

This work presents a new method to perform the fault-tolerant estimation process, with the view to identifying the weld line existing in storage tanks, using α-β filtering and a data-based fault detection system based on discrete event theory. Such feature identification is very important when considering the need for frequent inspection of tanks used to store harmful products.

The system proposed was tested and the results presented in this paper provide a strong evidence of its applicability on weld line detection systems. The fault-tolerant estimation process, carried out based on the α-β filter, was capable to avoid the failures occurred in the experiment, to significantly reduce the measurement noise and to give a fault-tolerant estimation of the angular and linear velocity of the system.

As a future work, it is suggested the use of data fusion from different sensors to increase the data confidence. The use of sensors that work under different physical principles can also be considered to improve the state variable estimation process, thus allowing the handling of situations in which one of the available sensory systems stops working due to some kind of long-lasting failure, not supported by the system proposed here.

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