SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Executive Summary of the Thesis

Identification of Molten Aluminium Level through Vision System in Casting Furnaces

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'Automazione

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1. Introduction

In the continuous casting of aluminium the molten aluminium is fed from a furnace into an open mold. For the correct functioning of the process it is important to guarantee a continuous metal flow from the furnace. To ensure this it is necessary to provide measurements of the aluminium level inside the furnace. The accurate measurement of molten aluminium level in the continuous casting processes is a major issue which affects the final product quality and process efficiency [1]. The most common method used to determine metal level has been the use of sounding bars. In this method, a rod is periodically immersed into the molten metal bath. The metal level is determined visually by the operator observing the location of color change along the bar. Another traditional method consists in weighting the solid metal to predict the level once melted. Both methods provide limited accuracy and repeatability. Various alternative non contact techniques for metal level measurement inside a furnace or other metallurgical vessels like tundish and molds have been investigated and tested lately. These techniques include γ-rays transmission, thermal conduction, Eddy current, induction, capacitance and computer vision based methods. However γ-rays method uses radiations which are dangerous for human body. Thermal conduction and Eddy-current methods require installation precautions which limit accuracy. Induction and capacitance techniques used for molds are unsuitable for installation inside a furnace since the harsh conditions would disable the sensors. Computer vision based methods found in literature aren't completely non-contact since they still need interaction with the melt. This work presents an alternative method for the measurement of aluminium level inside a furnace, which makes exclusive use of a camera vision system. The objective is to measure the level by detecting the interface formed by the molten aluminium surface with the furnace's refractory walls. The method makes use of well known machine vision techniques for edge and line detection known as Canny detector [2] and Hough transform [3]. Different alternatives have been investigated regarding pre-processing and edge detection techniques for a total of 4 approaches of the method. Here are presented the two which gave the best results. The set objectives are a robust on-line level detection in different illumination circumstances and the ability to provide reliable measurements of the molten aluminium level with uncertainty in the order of ±5 mm. The system is expected to perform well for good illumination conditions.

2. Proposed Method

For the proposed method a camera is used to capture the internal situation in the furnace. The algorithm uses Hough transform [3] to detect the line in correspondence of the melt surface/wall interface. Once the line is identified, the known dimensional relations between furnace features is used to derive a measure of the height of the level.

2.1. Setup of the system

The vision system is composed of a camera specifically designed for high temperature environments which is installed in a refractory wall of the furnace. The camera is provided with a 8 MP optical sensor (3840x2160 pixel) and lens with 49° x 65° view angles. The positioning study for the installation of the camera was performed through MATLAB simulations. The original AutoCAD drawings of the furnaces were used in order to identify the optimal position. The installation setup is shown in Figure 1. The camera is rotated of 30° towards the right refractory wall. The camera is placed at an height of 1400 mm as a safety measure in order to avoid molten aluminium splashes. In this configuration the camera is able to obtain an optimal view of the whole level excursion while also framing known features of the furnace. Before installation the camera was calibrated to estimate radial and tangential distortion.

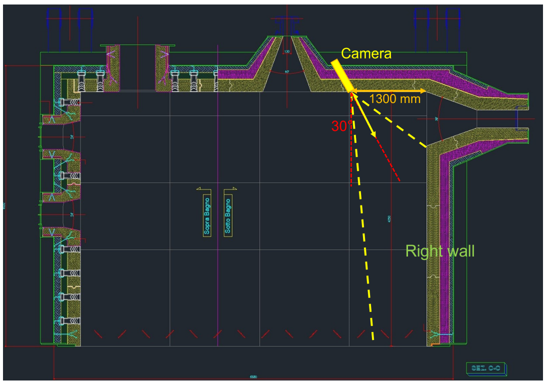


Figure 1: The camera setup inside the furnace.

2.2. Algorithm

The algorithm for level identification was developed using Python programming language. After installation in the furnace it was possible to connect to the camera's live stream. Sample videos of different working conditions were collected.

Pre-Processing

A pre-processing strategy was developed to prepare the images for edge detection. The level excursion occurs only in a restricted area of the frames so as a first step the images are cropped to size in order to reduce processing time. The final dimension is 600x750 pixel. Grayscale conversion is performed on the cropped frames. From testing it resulted that the images have very low contrast. Therefore the contrast is enhanced using a custom histogram modification technique which stretches the pixel intensities on a wider range. Edge detection techniques are easily affected by noise, so reducing the noise component in an image is fundamental. Tests were carried out with different classical noise filtering techniques [4][5]. From testing two techniques performed better, which are Gaussian filter and Bilateral filter.

Edge Detection

After the pre-processing stage the image is further processed to detect the edges. Edge detection is necessary to be able to apply the algorithm for line recognition. In order to obtain good quality edges Canny detector is applied to the pre-processed frames. Canny detector computes the gradient of the image and selects those pixels which correspond to gradient peaks. The output is a binary edge map where the white pixels correspond to the edges. It was observed that Canny detector was able to detect even weak edges in the images. The two thresholds used by the method were tuned with a process of trial and error.

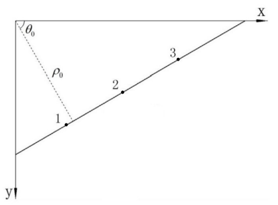
Line Detection

The edge map obtained is the input for the algorithm that performs Hough transform. The Hough transform is the most widely adopted technique for line detection in machine vision.

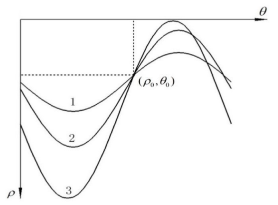
A line in the xy image plane can be described in different ways. Hough Transform uses a parametrization of the line known as normal form:

$$\rho = x \cdot cos(\theta) + y \cdot sin(\theta) \quad \text{-90°} \leq \theta \leq 90° \quad (1)$$

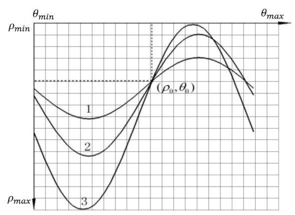
The geometrical interpretation of ρ and θ parameters is illustrated in Figure 2a. Notice in Figure 2b that a point (x_i, y_i) in the xy image plane is transformed in a linear combination of two sinusoids in the so called parameter space.



(a) xy image plane. Three aligned points on a line in the image.



(b) Parameter space. Transforms of points 1, 2, 3 intersect in a point which correspond to the parameters of the line in common.



(c) Discrete parameter space.

Figure 2: The principle of Hough Transform.

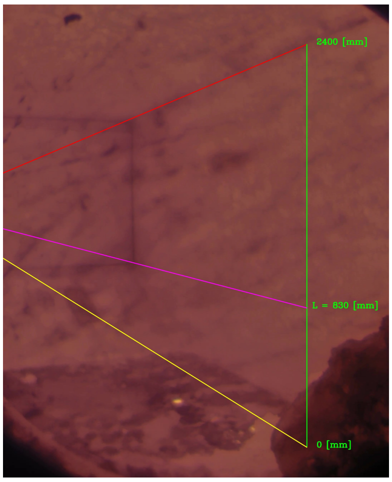
The parameter space is discretized in the practical implementation of the algorithm so more lines in image plane correspond to a single cell (Figure 2c). The resolution of the cells is set to 1 pixel for ρ and 1° for θ. The algorithm returns a vector which stores the detected lines. Each line is given in the form of its relative ρ and θ parameters.

Level Measurement

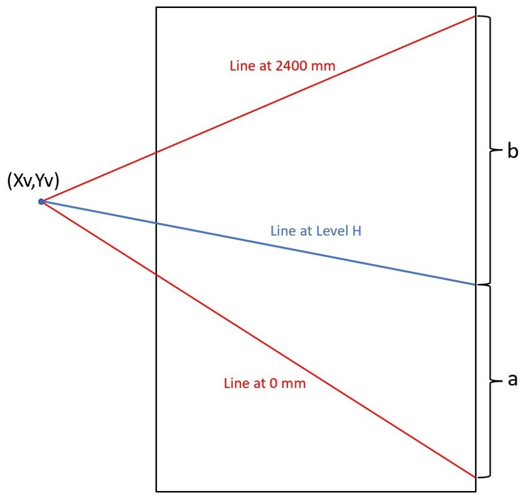
The proposed measurement reference system is based on the knowledge about dimensions and poses in 3D space of the furnace's features which are framed in the camera view. Perspective projection of parallel furnace's features is used to map the dimensions in the image plane. The obtained reference system is depicted in Figure 3a. With reference to Figure 3b the formula to compute the height from a detected line is a proportion:

$$H \text{ [mm]} = \frac{a}{a+b} \cdot 2400 \text{ [mm]} \qquad (2)$$

where a and b are measured in pixel.



(a) The reference system in the image.



(b) Level measurement principle.

Figure 3: The measurement reference system.

In general the Hough algorithm does not find a single line in the edge map but detects a few in correspondence of the level. A procedure for the selection of a single line has been developed. The melt level in the furnace is known to change with slow dynamics with respect to the acquisition rate. The algorithm keeps in memory the heights computed in 10 previous frames and determines the mean value. Then the height is computed for all the lines detected for the current frame. The line with height closer to the mean value is selected.

Testing

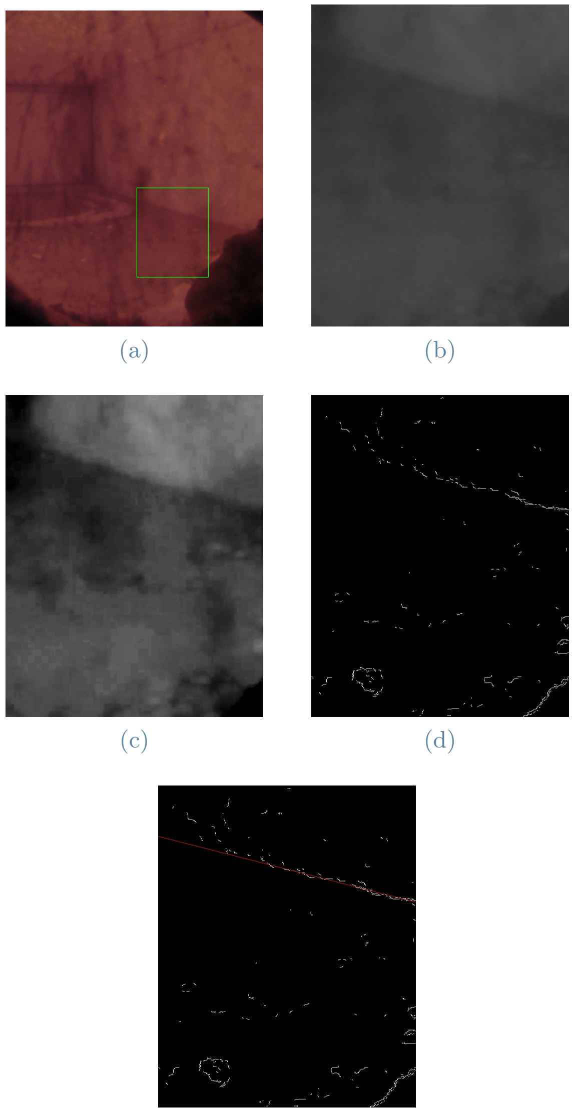
As explained in the introduction, 4 approaches were evaluated. Here we discuss the two which gave the best results. The two approaches only differ in the pre-processing technique used for noise reduction: First approach uses Gaussian filter while second approach makes use of Bilateral filter. The tests were performed on videos ranging different illumination conditions and evaluated measurement accuracy, robustness to light conditions and execution time. The type A measurement uncertainty for the two approaches was evaluated on a video in which the melt level is assumed to be constant. A second video has been used to evaluate the dynamic performances in terms of robustness to illumination changes and tracking of the level variation. In this video the level is rising and different light conditions are present. The light conditions change approximately between 75 s and 105 s. Moreover the front panel of the furnace starts opening at 203 s, which implies the shutdown of the burners. The mean execution time for the analysis of a frame was computed as the mean of the execution times of the whole frames data-set.

3. Results

The results of the experimental tests performed during the course of the research are presented in this section.

3.1. Image Processing Results

Figure 4 shows the result from application of the algorithm to a frame. Figure 4a shows a full size RGB capture from the camera. The green rectangle indicates the portion of the image which is processed. Figure 4b shows the frame after it has been cropped and converted to grayscale. In Figure 4c the frame after contrast enhancement and de-noising is shown (Bilateral filter is used in this case). Figure 4d depicts the edge map obtained from application of Canny detector. Figure 4e shows the result from application of Hough algorithm. The detected line is highlighted in red.

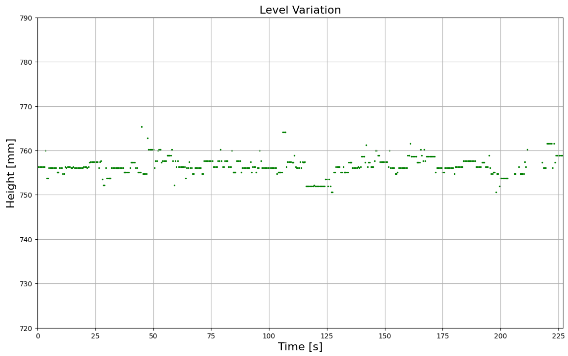


(a) (b) (c) (d) (e)

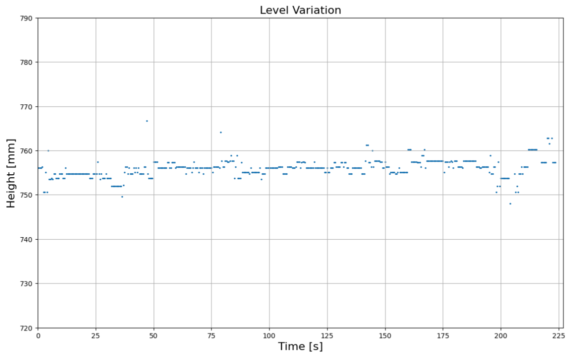
Figure 4: The processing sequence performed by the algorithm. (a) Full size RGB frame (green rectangle indicates the part for processing), (b) Cropped grayscale frame, (c) Frame after contrast enhancement and noise reduction (Bilateral filter is shown here), (d) Canny edge map, (d) Lines detected with Hough transform.

3.2. Measurement Uncertainty Results

The results of the measurements performed on first video for the two approaches are plotted in Figure 5. Table 1 contains measured mean value and measurement uncertainty. Two Gaussian distributions with the obtained mean values and standard deviations are plotted in red dashed line over the measurement distributions in Figure 6.

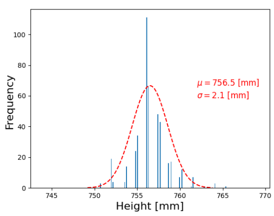


(a) Plot of level measured with approach 1.

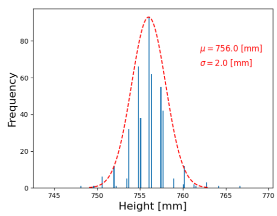


(b) Plot of level measured with approach 2.

Figure 5: Plots of the level measured for the 2 approaches. (a) Approach 1: De-noising with Gaussian filter, (b) Approach 2: De-noising with Bilateral filter.



(a) Approach 1 distribution.



(b) Approach 2 distribution.

Figure 6: The two measurement distributions.

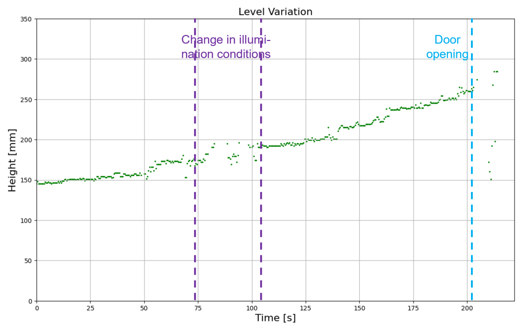
	Mean	**S.D. σ**	u_A **k=3**
Approach 1	756.5 mm	2.1 mm	6.3 mm
Approach 2	756.0 mm	2.0 mm	6.0 mm

Table 1: Mean value, standard deviation and measurement uncertainty. Approach 1: Gaussian filter. Approach 2: Bilateral filter.

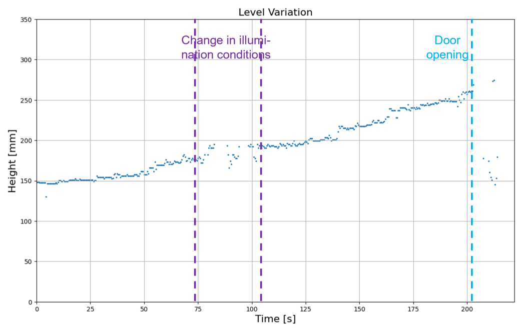
The mean values computed for the two approaches differ by 0.5 mm. Type A uncertainty is given with confidence level **k=3**

3.3. Dynamic Performances Results

The measurement results from the tests performed on the video with rising level and changes in the illumination conditions are shown in Figure 7. The time window where the light conditions change in the video is highlighted by two dashed lines (in purple). The instant when the front door starts opening is highlighted with the dashed line in light blue. The measured heights for the 2 approaches show a rising trend. In the purple window the measurement points are sparse as well as after the opening of the door.



(a) Plot of level measured with approach 1.



(b) Plot of level measured with approach 2.

Figure 7: Measurements of rising level for the two approaches.

3.4. Execution Time Results

The algorithm's mean execution time for a frame was computed averaging the execution time of 898 frames. The results are collected in Table 2.

	Mean Execution Time
Approach 1	325 ms
Approach 2	369 ms

Table 2: Mean execution times.

4. Discussion

4.1. Image Processing

With reference to the results in 3.1 it is pointed out that for the purpose of line detection it isn't necessary to use the whole image. As shown in Figure 4a the level excursion can be observed in a reduced area. This makes it possible to reduce the elaboration time since the number of pixel in the green rectangle is approximately 1/18 of the total. Figure 4b shows the cropped frame after grayscale conversion. It is evident that the contrast is poor. The level edge is barely visible. This motivates the need for contrast enhancement. In the frame in Figure 4c after contrast enhancement and noise reduction (Bilateral filter in the example) the level edge is more visible. with Canny detector it was possible to obtain thin edges as shown in Figure 4d. The edges however aren't continuous. Still, this is an acceptable edge map considering that in the image in Figure 4c there isn't a steep change of intensities in correspondence of the level. In Figure 4e it is noticed that however the edge map is sufficient for the Hough algorithm to detect lines.

4.2. Measurement Uncertainty

In the video used to estimate measurement uncertainty for the two approaches the level is assumed to be constant. Reference is made to the graphs in Figure 5. It is noticed that the graphs of both approaches appear coherent with the analysed video. The measured heights in fact follow a trend which is constant (with small fluctuations). In confirmation of this the distributions of the measurements from approaches 1 and 2 shown in Figure 6a and 6b are well described by Gaussian distributions. In both distributions it can be observed that there are gaps of approximately 1 mm between the columns. This effect has to be attributed to the discretization of the parameters space performed in the Hough algorithm. With regards to the effect of the pre-processing choice it is noticed that approach 1 which uses Gaussian blur has a slightly higher standard deviation with respect to approach 2 which uses Bilateral filter. The results reported in Table 1 show that minimum value for uncertainty is 6.0 mm and is obtained with approach 2.

4.3. Dynamic Performances

The results from approaches 3 and 4 show some sensitivity to the change of illumination from 75 s to 103 s (Figures 7a and 7b). However the measured heights in that window seem coherent with the trend of the measurements in the other intervals. It is noticed from comparison that robustness to light conditions has very small correlation with the choice of the pre-processing filter (Gaussian or Bilateral). In the last part of the video at 203 s the front panel of the furnace opens which implies the shutdown of the burners. The light intensity levels become very low. As would be expected both approaches are no more able to detect borders. Overall the dynamic performances of the two approaches are similar.

4.4. Execution time

Mean execution times for the two approaches are comparable (Table 2). The slightly higher time of approach 2 with respect to 1 is due to the extra time required by the Bilateral filter.

5. Conclusions

The proposed method has been proven to be capable of detecting aluminium level in different operating conditions. The two presented approaches resulted to meet expectations. Canny detector resulted to be robust enough to moderate changes of lighting condition. The set objective to obtain measurements with uncertainty in the order of 5 mm was reached by both approaches 1 and 2 with uncertainty of respectively 6.3 mm and 6.0 mm at k=3. Both approaches have been considered suitable for on-line monitoring of the aluminium level inside the casting furnace. As expected the methods performed well when the illumination conditions were met. A future improvement could be the implementation of an algorithm for the adaptive adjustment of shutter speed based on illumination conditions.

6. Acknowledgements

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References

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