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Reading of an Analog Liquid Level Gauge on an Oil Platform with a Mobile Robot using 2-D Images

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***Abstract*— An approach to automatically read oil platforms' liquid level gauges, originally designed to be read by human operators is presented in this paper. Grayscale image data is acquired from different heights to enhance reliability and minimize deviations due to outdoor influences like reflections and translucence. The position of the level gauge in the scene image is determined, the liquid column is extracted and the level of the liquid is returned using image processing methods.**

I. INTRODUCTION

Measuring the level of a liquid in a container is seen as a solved task. However, as the gauge may not be altered in any way, conventional methods of detection using ultrasonic, magnetic, mechanical, pneumatic, conductive, microwave or capacitive sensors cannot be applied. New optical methods as reciprocally placed photo-LEDs and transistors described in [1] look promising, but as there is no possibility to reliably get behind the gauge, the sensor chosen here is a 2-D camera. To acquire the liquid level of the level gauge a mobile robot (fig. 1) approaches the level and captures the gauge taking images. Although camera based level detection is already greatly described e.g. in [2], not having a closed environment with a correctly positioned bottle on a conveyor belt, brings a big increase in complexity similarly found in [3], [4] and [5]. Coping with different lighting, reflections, backgrounds, objects shining through or alternating weather conditions and locating the level gauge in the scene image brings new additional challenges.

The acquisition of the level is done in three consecutive steps. First the position of the level gauge in the image is determined. To improve the reliability of the following level reading and reduce influences as reflections or translucence of objects in the background, that can be seen in fig. 2, this step is performed repeatedly using different images.

Compared to tests with polarized filters and usage of a flash combined with a very short aperture time of the camera's shutter, using multiple scene images makes the biggest enhancement in readability and reproducibility of the same quality. Images of the same level gauge are taken from different angles. As the level is a horizontal feature, horizontal disturbances have a much higher influence than vertical ones and are to be compensated. To achieve this the height of the camera is altered. Secondly warped images of the liquid column are created giving optimal conditions for level detection. Based on these images an estimation of the level follows accepting multiple level hypotheses for each column.

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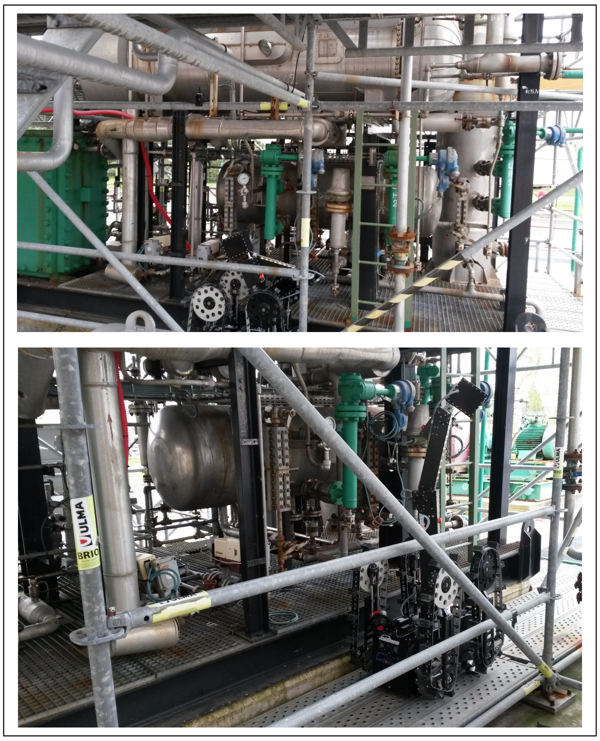

Fig. 1. Mobile robot approaching the liquid level gauge and positioning its arm to take a picture for level detection using image processing.

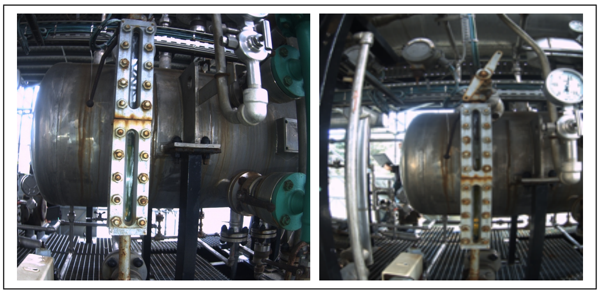

Fig. 2. Reflections (left) and translucence of a pipe behind the liquid level gauge (right) are examples for challenges for a correct reading.

II. METHODS

Fig. 3 shows the structure of the proposed method. Due to preprocessing steps in other parts of the overall code, grayscale images are the basis for the detection. Changing colors of the liquid in the gauge make RGB images of minor importance. The position of the level gauge in the 3D space is known and the pose of the mobile robot and its arm can be

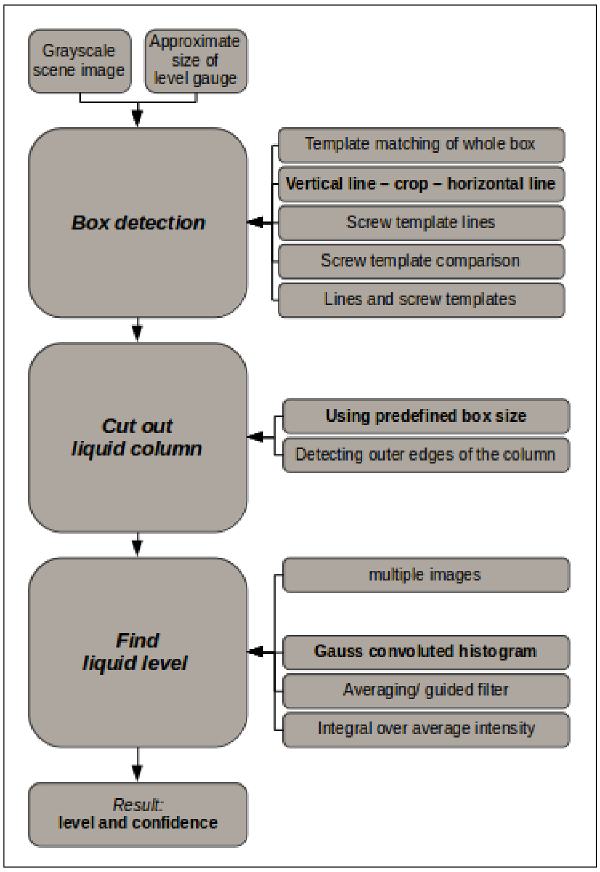

Fig. 3. Structure of level detection

approximated quite well using sensor data. Therefore the size of the box can be estimated and used for further processing.

A. Box Detection

As the outer box of the level gauge has hardly any unique features, tests applying feature-based algorithms like SIFT did not bring the results intended. To robustly find the correct location of the box a combination of five approaches is used. For implementation on the robot all five are combined comparing their returned edge points of the box as well as their confidence values. Thereby maximum knowledge of the accuracy of the detected box position in the image can be achieved, that is crucial for further processing and for a final output of a confidence value of the reading.

The straight forward approach is template matching, using an image of the whole outer box as a template. The box template is resized using the height of the box in the scene image. Fig. 4 shows, that this works nicely for scenes, where the expected height has just minor deviations from the real one and the image is taken frontal or is made looking like a frontal image by warping in detection preprocessing. This keeps the influences of distortion and rotation low. Furthermore lighting conditions should be similar.

The second approach focuses on detecting the outer lines of the box based on Canny edge detection [6] and Hough line detection [7]. Varying the parameters of edge detection and just taking the hough lines that are roughly vertical,

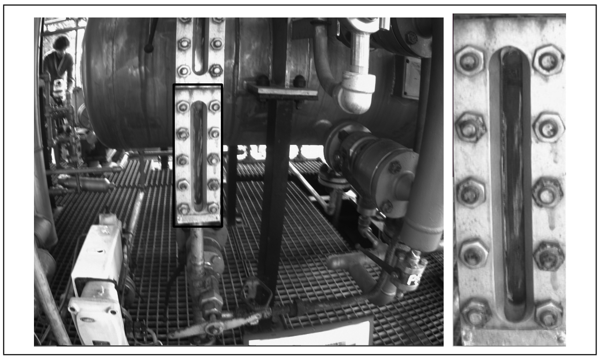

Fig. 4. Detecting the outer box with basic template matching works for ideal conditions.

i.e. within a certain angle threshold, gives possible lines for the left and right border of the outer box. Using further knowledge about the structure of the level gauge the final vertical border lines are found. The upper and lower line of the box are not as present in the image. The horizontal lines containing the most points in the Canny image rarely concur with those vertical box borders. To overcome this, the scene image is cropped on the left and right side using the found vertical borders. As the grayscale image recieved from prepocessing steps is often warped, there sometimes occurs a black part at the top and bottom of the scene image. If that is the case, the horizontal lines standing out most are the transitions between the real image and the black parts. To solve this, the black parts at the top are filled with the same intensity as the uppermost pixels of the real scene, that can be seen in fig. 6. The black parts at the bottom are filled with the same intensity as the pixels at the bottom of the real scene image. In the new image the protruding horizontal lines are the upper and lower box borders. To make sure to correctly distinguish the horizontal borderlines from other remaining horizontal lines within the cropped image, again knowledge about the structure of the liquid level gauge is used. The four intersections of the vertical and horizontal border lines are returned as box edge points. If the box dimensions are given, they provide a further constraint to reliably detect the vertical as well as the horizontal lines and find the correct borders.

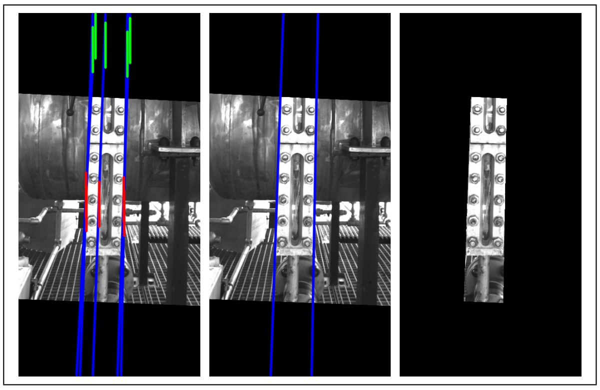

Fig. 5. Attain vertical borders of the box

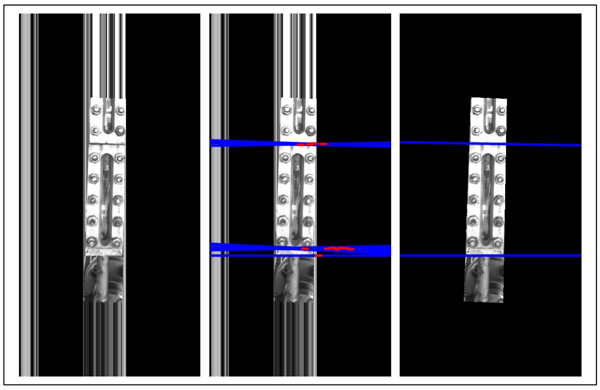

Fig. 6. Attain horizontal borders of the box

In the third approach that can be seen in fig. 7 advantage is taken of the texture of the level gauge. Besides the metal box and the liquid column in the middle it consists of ten big screws arranged in two vertical lines. A set of screw images is used for template matching and detecting possible screws in the scene. The concept is to deliberately look for more than ten screws and then classify them into so called good screws, that do belong to the gauge, and bad screws, that do not. This is done by creating a new black image, where the center of every found screw is marked as a white pixel. If a pixel is already white, the one below is made white instead to make it count. Afterwards Hough line detection is applied in this binary image to find lines of screws. The two lines with most participating pixels are used to finally determine the position of the box. Knowledge about the maximum amount of screws or about their similar vertical distance can be used to optimize the result.

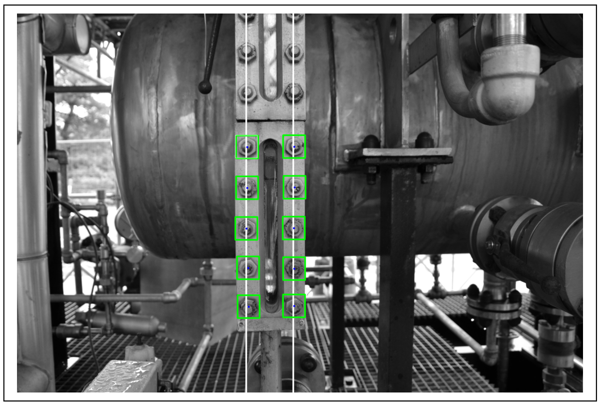

Fig. 7. Attain the position of the outer box by using template matching to find screws of the box. More than the existing 10 screws are to be found to then form lines of screws.

If the height of the box is given, the fourth approach can be applied. Similar to the third approach white dots are created in a black image for found screw templates. However, the white dots for found screws are made bigger and compared to an image created in the algorithm, consisting out of ten big white filled dots. Those are placed exactly on the spots, where a level gauge of the given size has located its screws. The comparison is done by sliding the artificial ten dot image over the scene image and adding one to the correlation variable for each pixel that is white in both images. The point with the highest correlation marks the estimated position of the level gauge's outer box.

To combine the strengths of the algorithms mentioned above, the fifth option is based on line detection of box borders and template matching with screws. Instead of getting just the two best vertical lines, more of them are to be found implementing a Canny edge detector and Hough transform. Next screw templates are found in the scene. Lines, as well as screws are then graded identifying their relative horizontal distances. There have to be a certain number of screws in the vicinity of a line, to mark both of them as good. Fig. 7 shows, how finally good screws and lines are marked in green, other discarded ones in blue and bad ones in red.

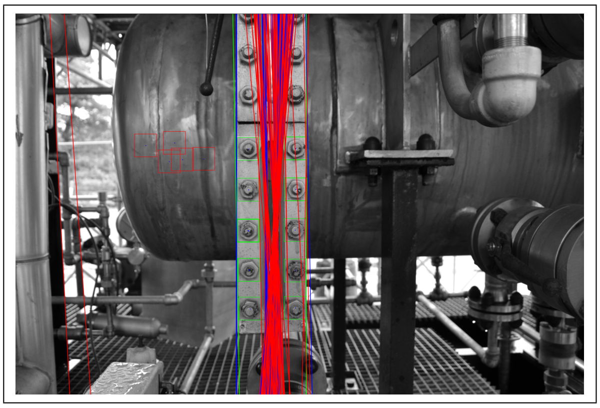

Fig. 8. Combine the use of template screws and line detection to optimize the result.

B. Cut-out of Liquid Column

The combination of the box detection methods above lays the foundation for localizing the inner liquid column and cutting it out. As the result image of the box detection contains just the box, the position of the inner liquid column is acquired using height and width of the column in respect to the box size. As the appearance of the box is known, the outer edges of the column are searched for in a specific area, to get detailed borders.

C. Level Detection

Having acquired and cut out the liquid column, the level is obtained. Allthough there are many different kinds of disturbances when detecting the liquid level, reflections and translucence are the ones affecting the reading the most, as described in fig. 2. Horizontal reflections of the sun or nearby objects create horizontal lines, that often are even more prominent than the real water level. Pipes or other objects behind the liquid level gauge also create horizontal gradients in the intensity image of the liquid column that is used to obtain the correct level. To overcome these disturbances, images of the gauge are taken from different heights.

As the mobile robot's arm is restricted to five degrees of freedom, the normal pose of the camera mounted on the arm has to be altered. To achieve readings from different heights, the camera has to turn around its lateral axis. Beside this pitching movement it needs to move along the vertical axis as illustrated in fig. 9. These movements result in images taken from different heights, where the reflections and objects behind the liquid level gauge move vertically in respect to the liquid column itself. However, the level of the liquid remains at the same height within the column (see fig. 10).

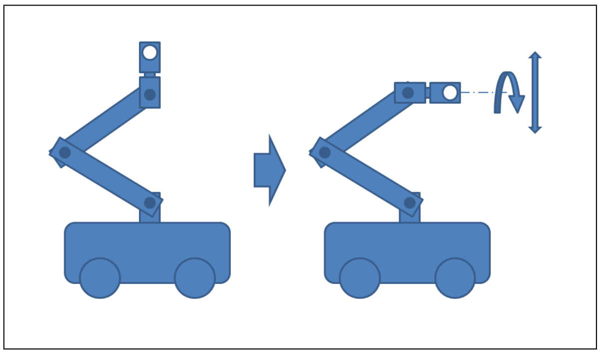

Fig. 9. Robot pose to achieve readings of the liquid level gauge from different heights (Camera has to turn around the lateral axis, i.e. pitch and has to move along the vertical axis.)

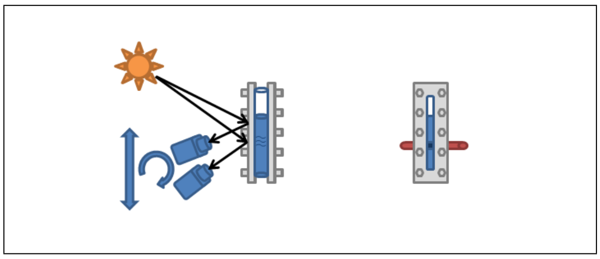

Fig. 10. Taking images from different heights to make reflections and translucence of objects behind the gauge move vertically while the actual liquid level remains at the same vertical position

As for box detection, reliability of the reading is of higher importance than speed. Hence three algorithms for level detection are performed and combined resulting in a final value and confidence.

The obvious method is the detection of the most outstanding horizontal line. Canny edge detection is used, Hough transform is applied and only lines within a certain angle threshold are considered. However, this first part of level detection is not restricted to find just one line, but multiple ones. The reason for accepting multiple level hypotheses for one column is that there can be found horizontal lines within the column that have nothing to do with the real liquid level.

The y-positions of the detected level hypotheses are then normalized between 0 and 100 and subtracted from 100 to get the liquid levels in percent. The whole range from zero to a hundred percent is divided in equally sized intervals and a histogram is created. Each level hypothesis in the histogram is then convoluted with a Gauss function. This takes into accout that there might be slight deviations of the real level position in the liquid column images that are cut out in the box image, that is detected and cut out of the original scene image. Fig. 11 shows that the histograms with Gauss filtering are created out of every column image and summed up. To optain the real liquid level, the position of the maximum of the resulting function is found.

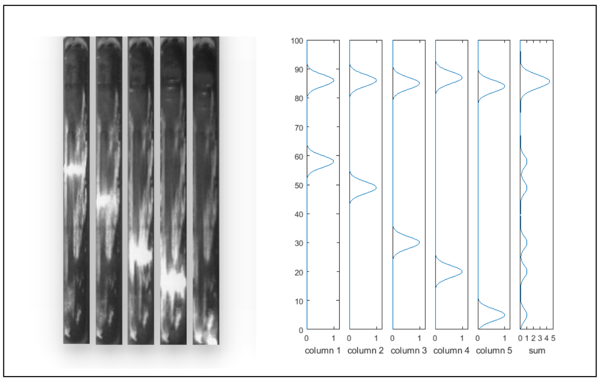

Fig. 11. Liquid columns with reflections at different heights. The strongest gradients are represented with Gauss functions and added. The final level is obtained by finding the maximum of the sum of the functions describing the columns.

The second option gets the average intensity for every horizontal row of pixels in the column image. This array of intensity values having the size of the number of rows in the column image is smoothed with a filter and the following level detection algorithm is performed. All intensity values are normalized to have a maximum value of 1. Starting from the top, a separator divides the intensity values in two parts. Then two integrals are obtained. On one side the integral above the curve is used, on the other side of the separator the integral below is used. As the lower part of the liquid column contains the liquid, it is expected to have the higher intensity. Nevertheless, it is also done the other way round to achieve safe results. The sum of the two integrals is stored in a new array for each position of the separator. The position, where the sum becomes a maximum is selected as the result for the level detection.

III. Experiments

A. Box Detection

Images are taken by the robot outdoors under very different weather conditions. Evaluating the template matching approach, it can be shown, that the more the illumination and weather resemble the conditions on the template image, the better it works.

When performing approaches three to five, it becomes obvious, that according to different sized boxes in the images, the template screws have to be adapted, thus resized to perfectly fit the screws in the scene image. To cover not just frontal images of the level gauge but also those taken from slightly above and slightly below the height of the box center, also screw templates have to be chosen accordingly. The set of templates has to contain screws photographed from different angles.

When running the different algorithms for box detection, it showed that every single one of them has its strengths and weaknesses. Different approaches perform best depending on illumination, weather condition, distance of the camera to the level gauge or resolution of the image. As the correctness of the reading and the declaration of the confidence of the final value are of particular importance, performing different approaches and a subsequent comparison are worth the additional time needed.

Running tests of the algorithm on the real robot on an oil platform training site it became apparent, that the underlaying algorithm that takes images of the level gauge returns images with low deviations of the box position from the image center. On average the probability of the box being close to the center of the scene image is much higher than it being close to the edge of the image. Taking this into account, the confidence of the detected box being correct is multiplied with an additional function

$$1 - \frac{c}{100}\sqrt{\frac{(w/2-x)^2+(h/2-y)^2)}{(w/2)^2+(h/2)^2}}$$

where w is the width and h is the height of the scene. x and y define the center-point of the found box. c is a constant giving the percentage of how much the confidence is lowered if the box center is in one of the corners of the image, i.e. the box center-point with the biggest distance to the scene center that is still in the image.

Using screw templates worked best for high resolution images and only slight differences in size and illumination. The approach for box detection based on finding the correct border lines outperformed this method when the image had a low resolution. Fig. 12 shows the results of box detection for six different images, that are used to get the correct waterlevel. Fig. 13 shows the cropped and warped boxes, for later getting the column images.

B. Cut-out of Liquid Column

Tests have shown that the precision and correctness of cutting out the liquid column of the level gauge highly depends on the preceding box detection. Having detected the outer box with an error less than ten percent of its width, ensures a high probability of getting a correctly cut out liquid column as a basis for the following level detection.

C. Level Detection

After testing with a halogen work light serving as an artificial sun and a model of the level gauge, images taken in the real environment with sunlight show the same results. As images of the level gauge have been taken from five or six different heights, they now have to be arranged in a way they can be compared to each other. Using one column image as reference the other column images are fitted by subtracting intensities while slightly shifting the column image to fit. Multiple checks with small changes in size improve the result.

Applying the Histogram-Gauss-Adding method on images that are taken from different heights delivers good results. To verify the algorithm also sets of images with many scenes with high intensity gradients at the same height are tested. Fig. 14 shows the liquid columns cut out of the boxes in

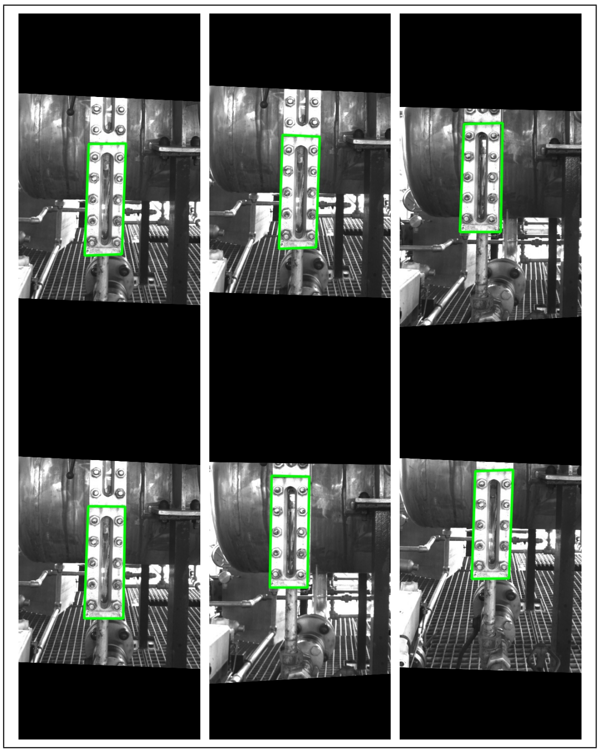

Fig. 12. Box detection in multiple images of the scene that are used to obtain the liquid level

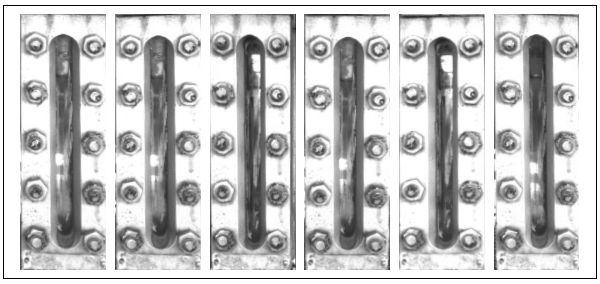

Fig. 13. Resulting box images for liquid column extraction

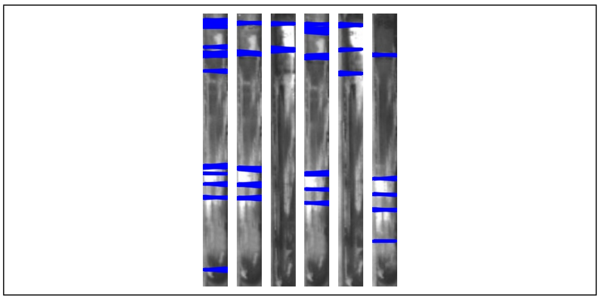

Fig. 14. Extracted liquid columns with multiple level hypotheses (Despite the fact that four out of six images have similar positions of the reflections the correct level is still found.)

fig. 13, that originally belong to the scenes in fig. 12. It can be seen that there are a lot of wrong level hypotheses at approximately the same height. However, as more column images contain correct level hypotheses, the correct ones predominate and the real level is returned.

Test have shown that the Histogram-Gauss-Adding method described above mostly outperforms approaches like creating an average image as in fig. 15 using

$$i_x = \frac{1}{n}(i_{x_1} + i_{x_2} + \ldots + i_{x_n}).$$

On the right side of the original image, images show the same situation photographed from different heights with the column already identified and cropped. In the following images the original columns are added equally weighted with linear blending. First the first two columns are added, then the first three, then the first four and in finally all five of them are put into one single image. The found level is marked in red. This clearly shows, that reflections can be suppressed using multiple images taken from different heights. Further improvements are reached using a guided filter. The middle one of the column images is used as a guidance image for this edge preserving filtering method. However, this approach only works for perfectly alligned images. Therefore it is just used to raise the confidence of the reading, if it delivers similar results as the method using Gauss functions.

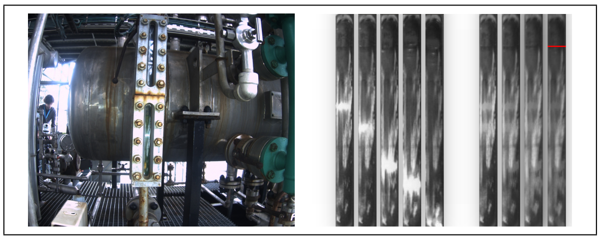

Fig. 15. Scene image with reflections in the liquid column, extracted liquid columns from images taken from different heights and addition of 2,3,4 and 5 column images

Doing tests to compare the different level detection algorithms it can be seen that everyone of them has its advantages that make it reasonably useful for a reliable detection. Line detecting algorithms have their strengths in transparent liquids similar to water. The integral over the intensity array performs best for liquids that give a big intensity difference compared to the empty part of the liquid column.

IV. CONCLUSIONS

The initial task of detecting the liquid level of an analog gauge was reached using an algorithm for locating the outer box in the image, based on canny edge detection, hough line detection and template matching. The level was then obtained identifying the horizontal gradients standing out most. The crucial enhancement of the reliability of the process was achieved using multiple images and creating a sum of Gauss functions, each at the position of a level hypothesis. Disruptive effects of sunlight, rain and even objects like pipes shining through can be handled. Despite being cheaper and easier to implement than solutions with flashlight, polar filters or spectral filters, the reached confidence value of the reading can be increased drastically by a small additional arm movement of the robot, taking multiple images. Future detection algorithms may base on this approach to detect other kinds of reflective objects in outdoor conditions.

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