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A COMPUTER VISION SYSTEM FOR ESTIMATING AND CONTROLLING THE WEIGHT OF GLASS GOBS DURING THEIR INDUSTRIAL FORMATION PROCESS

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ABSTRACT (short: <150 words)

This paper presents a computer vision system for measuring the weight of gobs during a glass forming process, and a control strategy to correct automatically any weight deviation from a given set-point.

The system developed for measuring the weight of a gob is based on a reliable gob area estimation using image-processing algorithms. A monochrome CCD high-resolution camera and a photo-detector for synchronizing acquisition are used for registering gob images. Assuming that the gob has symmetry of revolution about the vertical axis, the proposed system estimates the weight of gobs with accuracy better than ±0.75%.

A learning weight control strategy is proposed based on a PI-repetitive control scheme. The weight deviation from a set point is used as a control signal to adjust the glass flow into the feeder. This regulation scheme allows effective weight control, canceling mid and long-term effects. The tracking error, ±1.5%, means a reduction of 40% when compared with a traditional PI controller.

Keywords: Glass Gob Inspection, Weight Estimation, Image Processing, Repetitive Control

ABSTRACT (<200 words)

This paper presents a computer vision system for measuring the weight of gobs during a glass forming process, and a control strategy to correct automatically any weight deviation from a given set-point.

The gob weight measurement system developed is based on a monochrome CCD high-resolution camera and a photo-detector for synchronizing the frame acquisition. The molten glass provides the illumination, so a high contrast image is obtained with a bright object and dark background. Several image-processing algorithms are presented for reliable area estimation. Assuming that the gob has symmetry of revolution about the vertical axis and uniform mass density, the proposed system estimates the weight of gobs with accuracy better than ±0.75%.

During the formation of molten glass gobs, several noise sources can cause a deviation in the weight from a predefined reference value. To solve this problem, a learning weight control strategy is proposed based on a PI-repetitive control scheme. The weight deviation from a set point is used as a control signal to adjust the glass flow into the feeder. This regulation scheme allows effective weight control, canceling mid and long-term effects. The tracking error, ±1.5%, means a reduction of 40% when compared with a traditional PI controller.

1. INTRODUCTION

Fabrication of glass is a complex industrial process, where the same production lines are employed in different manufacturing processes. Manual modifications are commonplace and are a time-consuming, intuitive task that is usually done by operators with great experience. An automated inspection and control system is proposed which can manage most routine operations.

In the production of glass dishes the key component is the feeder that transforms a continuous flow of glass into a discrete sequence of glass drops. The feeder (see figure 1 right) consists of a cylinder that can be moved vertically to regulate the gob size, a piston used to push glass out, and a shear mechanism to cut the molten glass to obtain the gobs from which the plates are formed. In the fabrication process, control is done by manually moving the cylinder up and down to change the glass flow. It is important to remark that the cylinder rotates periodically with a period that expert operators adjust empirically. Gobs fall down over molds, and dishes are shaped by centrifugal forces.

Several factors can cause a deviation of the weight of gobs from a predefined reference value. First, there is a random perturbation caused by the lack of synchronization of mechanical devices such as plungers, pistons, etc. Changes in the spinning direction of the tube inside the feeder are necessary to generate a homogeneous composition of the molten glass and cause significant mid-term drifts that are quite periodic and repetitive. We have observed that the gob weight oscillates with a period that corresponds exactly with the rotation period of the feeder tube, and can be corrected by changing the vertical position of the feeder tube. Additionally, long-term drifts due to changes in the viscosity of the raw glass material affect the weight along several hours of operation.

All these effects result in glass products of varying weight and diameter. In current production processes, about 10% of the final goods have to be rejected because they don’t fulfill quality requirements, causing a decrease of efficiency and productivity.

There are different commercial systems that control weight, shape and temperature [1, 2]. Those systems are based on linear cameras and perform image reconstruction based on calculation of the speed of the falling gob. Some of them use a dual frequency infrared pyrometer to measure temperature in different points inside the gob. The weight control strategy is normally based on a PID (Proportional-Integral-Derivative) implemented in a PLC (Programmable Logic Controller), which actuates by adjusting the cylinder height or the plunger position.

We propose a system that uses a high-resolution matrix camera to capture a picture of the gob. This method allows a precise area estimation without the need of image reconstruction and gob speed estimation. Instead of using a simple PID for the final control we have developed a digital repetitive controller to predict the rotation changes of the feeder tube. A weight scale parallel to the production line is used to calibrate the system, giving the actual weight of some dishes taken approximately every sixty minutes. In the next sections we will give detailed information of the proposed gob inspection system.

2. PROPOSED GOB INSPECTION SYSTEM: PRINCIPLE OF OPERATION

The system we have developed can be divided in three different modules that can be studied separately: 1) weight estimation module, 2) control module, and 3) calibration module. Figure 1 shows those modules and the information flow among them when they operate together.

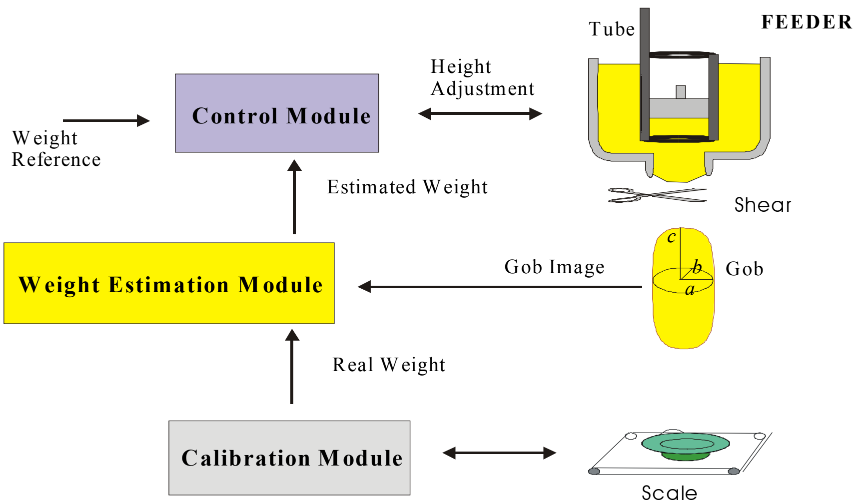

Figure 1. Gob Inspection System

The weight estimation module captures an image and executes an image-processing algorithm that is based on an intensity-level threshold for generating a binary image. Erosion and dilation morphological operators are used for reducing image noise. Region labeling and connection processes are used in order to distinguish pixels corresponding to the valid gob from other pixels forming significant background residuals that do not belong to the gob area. Once the area is estimated, the volume of the gob is derived, and consequently its weight, assuming a valid glass density value and a calibration value which is updated once every half an hour.

Control is made with estimated weight values and the position of the feeder tube. When the estimated weight deviates from the reference, the position of the feeder tube is modified in height via an AC motor. The achieved displacement is measured using a LVDT (Linear Variable Displacement Transformer) sensor. As we previously reported, the rotations of feeder tube produce weight perturbations, but this module uses a learning repetitive control to anticipate the response.

The Calibration module measures the real weight of dishes using a precision weight scale in the production line. A calibration constant is updated once an hour by comparing the real weight with weights calculated using the image processing software. This calibration constant integrates parameters that are not precisely known, such as glass density, focal length of the camera lenses, distance from the camera to the gob, and so on, and is used to match estimated weight with real values.

3. MEASUREMENT SUB-SYSTEM

The weight measurement estimation can be divided into the following steps: 1) Image acquisition, 2) segmentation and image improvement, and finally, 3) weight estimation. The next sub-sections give insight into these points.

3.1. Image acquisition.

To select a camera for image acquisition we used the following reasoning. We assume that we can approximate a gob by an ellipsoid with symmetry of revolution around its vertical axis. Assuming a typical gob weight of 410 grams with nearly constant density and a maximum error to be limited by ± 2 grams, the camera resolution must be at least 640x480 pixels. To avoid the use of complex sub-pixel algorithms [3, 4, 5], which are also more time-consuming, we have chosen a standard high-resolution 1026x1296 pixel camera (JAI CV-M1) which at one meter distance from the object plane gives a pixel size of about 0.1 by 0.1 mm.

When considering the gob as a moving object, it is necessary to take into account the integration or exposure time to use. Neglecting air friction, the velocity of the gob when it is in front of the photo-detector is independent of its volume. For a free-falling height of 0.5 meters the velocity of the gob is approximately 3 m/sec. In order to avoid a vertical displacement of the gob larger than the pixel resolution, that is, 0.1 mm, the exposure time should be less than 1/ 3000 s. This requirement is satisfied by JAI CV-M1 camera, which has an exposure time ranging from 1 second to 1/10000 seconds. The default operating temperature valid for our camera ranges between -5ºC and 45ºC, so in order to operate close to the feeder the camera is cooled using a fan. We have chosen an optical objective with a relatively long focal length (f = 35 mm) because this type of lens allows acquisition of images with low distortion, and it has no problems with limited depth of field, because distance to the gob is always constant.

To synchronize the gob presence with the camera acquisition trigger, we use a sensor based on a photo-detector that generates a TTL pulse when it detects an intense source of light. This pulse can be delayed in a range between 10 and 90 milliseconds in order to adjust the centering of the gob in the registered image. The sensitivity level of the detector can be adjusted to trigger the camera acquisition when enough illumination reaches the sensor. A black cylindrical head is attached in front of the photo-diode to let enter only light coming along the cylindrical major axis of the photo-diode. Therefore, light coming from any direction other than this axis is blocked, thereby eliminating additional light sources in the surrounding working-space that could cause false triggers.

We tested also the acquisition of two different views of the same gob using some catadioptric elements [6], in order to have as much information as possible to compensate any asymmetry. Experimentally, we found that the revolution symmetry of the gob is so high that using two views is redundant. A single view image is displayed in Figure 2. Some dark spots appear on the object, due to shear lubricant droplets, and some bright areas appear on the background due to specular reflections on some shiny metallic feeder parts.

In the field of sub-pixel estimation, it is known that the accuracy of algorithms depends on the camera orientation with respect to the boundaries of objects [3, 4, 5]. It is recommended to place the camera so that its reference frame axes intercept the longitudinal axis of the object at 45º, in order to reduce the sampling pixel errors. If we would align the axis of the camera to the longitudinal axis of the gob, and consider a typical gob length of approximately 1000 pixels, the digitization error might be in the worst-case ±0.5% (±2 grams). In our application the camera is placed so that gobs always fall down with an angle between 1 and 3 degrees. This slight rotation is enough to reduce significantly sampling errors down to ±0.2 grams, which is reasonable.

3.2. Segmentation and improvement of the image

Before we can estimate the weight of the gob, it is necessary to segment the image, i.e. remove the background and extract the region of the image corresponding only to the gob. This segmentation task is usually done, especially for images with a high contrast, by binarization and requires the selection of a gray level threshold. In reference [7], different techniques are described to select the threshold that involve choosing a gray level *t*, such all gray levels greater than *t* are mapped into the object and the rest are mapped into background. When *t* does not depend on the gray level of (x, y) it is called global threshold and has the same value for all image points.

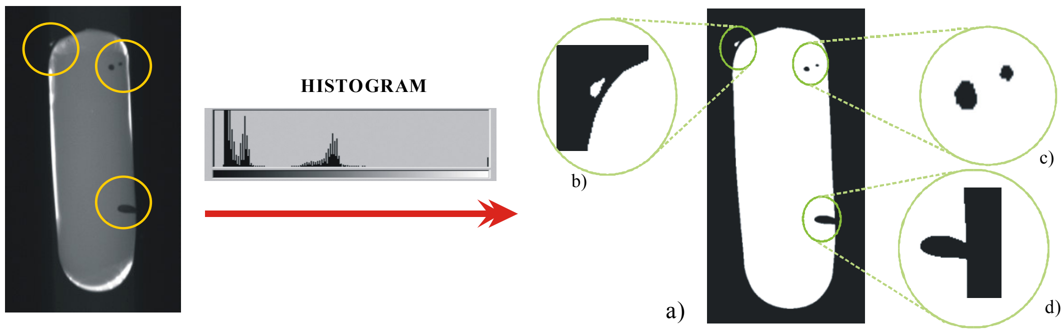

Figure 2. (Left) Intensity image and Histogram of a typical gob, (a) Binarized image, (b) Bright areas, (c) Dark spots, (d) Boundary holes

Plotting the histogram for a typical gob image (Figure 2), we see that there are three peaks, the two of them to the left correspond to background and the one to the right is the gob. We have seen that the optimum gray-level value to be used as threshold, which is computed using classical methods based on assuming that a histogram is formed by two overlapped gaussian distributions [7], performs worse than using a value selected experimentally. A threshold value of about 50, in an 8-bit intensity gray scale (0 is black and 255 is white), is a good choice for the type of images processed in our application. Once the image is binarized (Figure 2.a) we see that some dark spots and bright areas are still present. Bright areas (Figure 2.b) have a typical size of around 150 pixels, which can affect the final gob weight estimation by 0.46 grams. The dark spots (Figure 2.c) are different in size and their contribution to the volume depends on whether they are in the edge or inside the object. Those inside the gob region have an area of about 220 pixels (0.7 grams), but those in the boundary (Figure 2.d) are 350 pixel or higher (1.08 grams).

To obtain an image without bright areas, a region labeling process is executed. Once the image is labeled, we connect the regions belonging to the same object but with different labels. Now that we have a gob with no bright areas but with dark spots, we eliminate them using a morphological operator (closing filter) that concatenates two actions, dilation and erosion [11]. The dilatation function adds pixels to the boundaries of binary objects. This function will add pixels wherever pixels in the image intersect nonzero elements in the structuring element. The erode function removes pixels from binary objects in the same way that the dilation adds them. When the regions are expanded the dark spots inside the gob disappear, and after erosion spots are not regenerated. Occasionally, large holes close to the boundary will remain unfiltered.

3.3. Algorithms to obtain the weight

Now that we have a segmented image free of noise, we want an estimation of the gob weight. Assuming that gobs can be modeled as ellipsoids (see figure 1) because they have symmetry of revolution around the major vertical axis, *c,* and the gob horizontal cross-section is approximately a circle defined by the minor axes, *a* and *b,* then the expression to compute the gob volume is, $volume = 4/3 \cdot \pi \cdot a \cdot b \cdot c = 4/3 \cdot area \cdot b$. The area is estimated by counting all pixels set to one in the binary image. If we assume constant density, the weight of the gob is computed by this expression:

$$weight = density \cdot volume = cte \cdot area \cdot b \qquad \text{(eq. 1)}$$

Therefore the weight depends on a constant, *cte,* (including among others the glass density, focal length,…), the area of the gob in the image, and the semi-minor axis of the ellipsoid, *b*, which is not visible in the image. Note in eq. 1 that the *area* and *b* are dependent each other, so in fact weight depends not linearly with area. Considering that the size and shape of gobs do not change significantly, we can assume that *b* is quite stable and constant; therefore there is a linear relationship between weight and area.

$$weight = cte' \cdot area \qquad \text{(eq. 2)}$$

where, *cte'*, is a constant that depends on glass density, gob depth (*b*), optical focal length, distance from camera to gob, and so on. This constant is estimated from the real weight value provided by the calibration module (Figure 1 bottom), by a least square fitting.

3.4. Experiments and validation

The validation of the above-described algorithms is experimentally done by means of capturing 300 gob images and weighing the corresponding final dishes. The reference value of this particular product is 410 grams. In Figure 3.a the real weights are plotted together with a representation of changes in the spinning direction of the feeder tube. It can be seen how those changes, represented by the square-like plot (top and bottom of square-like plot means CW and CCW spinning directions, respectively), affect the real weight. The difference between real weight and the values obtained with the image processing algorithms is depicted in Figure 3.b, where it can be observed that the maximum error in the weight measures is ±3 grams. The RMS value for the measurement algorithms is 1.2 grams.

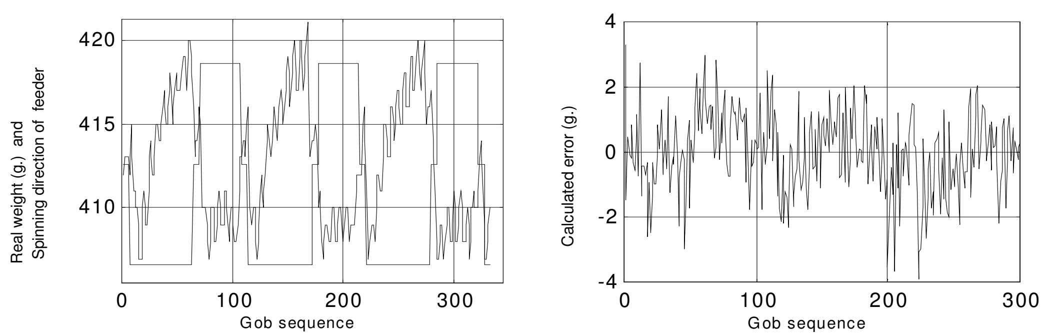

Figure 3. a) Real weight and CW (Clock Wise) and CCW (Counter Clock Wise) tube rotations, b) Difference between calculated and real weight

4. CONTROL SUB-SYSTEM

This section presents the description of the control module designed for weight regulation and mid-term disturbance cancellation. We present first the plant model identification procedure and after that the design of a controller based on the previously identified plant model.

4.1. Identification of the system plant

In our application, the plant to be controlled is the feeder, which we can consider as a SISO system where the input is the height of the feeder tube and the output is the weight of each gob. Other parameters such as glass temperature, tube rotation cycle, synchronisation of shear, and so on, are considered as disturbances.

In order to obtain the plant model, we excited the feeder with a set of step-like tube displacements, while the output of the plant was registered. Using Matlab's system identification toolbox and a sample period of 1 second, we found that the discrete transfer function has 4 poles (0.491±0.335i; -0.33±0.31i) and 4 zeros (-1.52; 0.629±0.735i; 0) on the 'z' plane. One of the four zeros (-1.52) is outside the unit circle so the plant model is a non minimum-phase system.

4.2.Control strategies

In this paper we have already described short-, mid- and long-term disturbances, which correspond to weight noise of different types: random white noise, periodic noise, and drifts, respectively. In Figure 4.a we illustrate short- and mid-term disturbances for the open-loop plant (the measured RMS disturbance is 10.1 grams) .

The control strategy we present aims to cancel the mid- and long-terms disturbances and does not cope with the random component which can be only diminished by improving the feeder design.

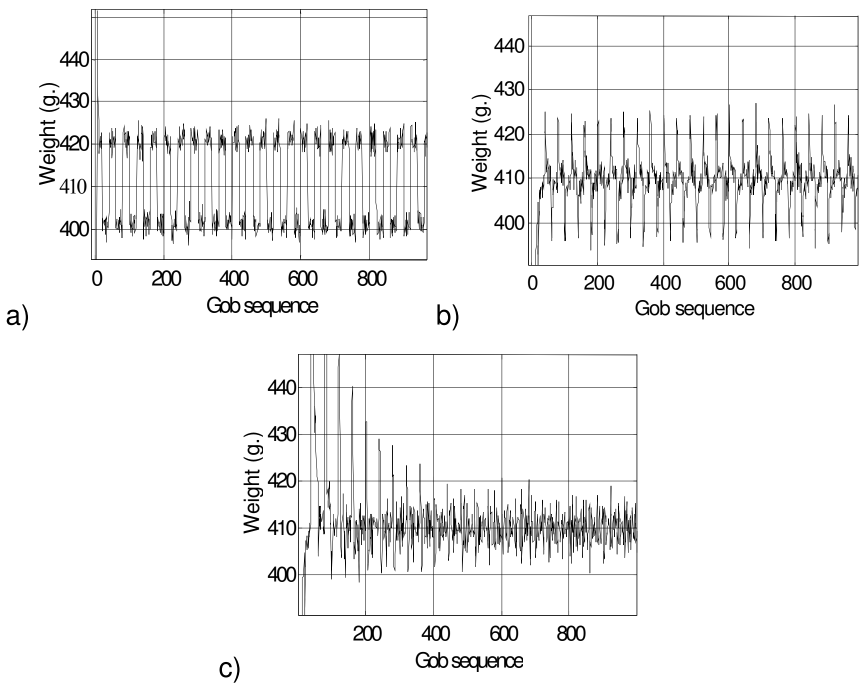

Figure 4.a) Open-loop response to a constant reference. b) PI control performance. c) PI-repetitive controls performance.

As can be seen in Figure 4.b, we have developed a PI controller to cancel long-term disturbances and some of the mid-term or periodic errors. The PI parameters (Ki and Kp) were selected to ensure stability under significant deviation between the plant model and the time-variant feeder plant. Those constants are Ki = 0.2 and Kp = 0.2. The PI controller eliminates long-term drifts and minimizes to some extent cyclic errors; the resulting RMS error is 6.27 grams.

A learning control strategy using a repetitive controller (Figure 5) is proposed, to improve the PI controller that is unable to cancel out all the cyclic disturbances. This type of control is especially appropriate for periodic disturbances, because it learns from previous cycles the control law to be generated in the future. Therefore, it is able to predict future perturbations anticipating the control action before the predicted disturbance appears [8, 9, 10]. The repetitive controller is represented by this discrete equation:

$$out_R\,(k) = out_R\,(k - M) + K_L \,.\, in_R\,(k - M) \qquad \text{(eq. 3)}$$

where k is an integer value representing discrete time at the sampling period T according to expression t=kT (T is approximately 1 second); M is the period of the cyclic disturbance in units of samples (typically M=40 samples); K_L is the learning constant that represents the speed of incorporating innovations into the learnt sequence (K_L= 0.5); in_R is the input to the repetitive controller which corresponds to the weight error (Figure 5, left); and out_R is the output of the repetitive controller that added to the reference weight is used as the reference to the PI closed-loop block (Figure 5, right).

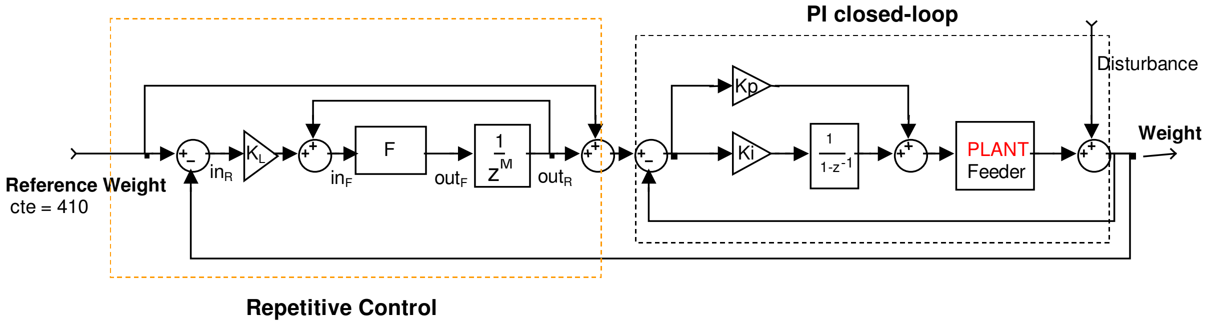

Figure 5. PI-repetitive control diagram

A zero-phase low pass filter, F, (see Figure 5) is used inside the repetitive loop to make the repetitive controller more robust against non-perfect periodic disturbances. This filter makes the controller less effective in case of periodic disturbances, so a trade-off between robustness and effectiveness is found. The z-transform of the selected filter is in discrete time:

$$out_F\ (k) = (1/6)\ .\ in_F\ (k + 1) + (2/3)\ .\ in_F\ (k) + (1/6)\ .\ in_F\ (k - 1) \qquad \text{(eq. 4)}$$

where k is again the discrete time, in_F is the input to the F filter, and out_F is the output of this filter.

The PI-repetitive control, as is show in Figure 4c, improves the response of the PI controller by itself, reducing most of the cyclic errors. The RMS value, 3.6 grams, represents about a 40% error reduction compared to the classical PI controller.

5. CONCLUSIONS

The most common sources of weight variation in the process of fabrication of glass plates have been analysed. An algorithm for weight control of the forming glass gobs has been introduced, and it is outlined as follows. As a first step we develop a module for measuring the weight of molten glass gobs based on image processing algorithms for estimating the area of these gobs. The segmented images are obtained by binarizing the acquired intensity images by a fixed threshold. Image noise is reduced using erosion and dilatation morphological operators and applying region labelling and connection techniques. The estimation of the gob weight, which is derived from the area of the gob, is fed into the control loop. Typical weight estimation has a RMS error of 1.2 grams (±3 g.), which for a usual product weight, accounts for only a ±0.75% deviation.

Using the estimated gob weight and the reference value of each product, a learning repetitive control scheme is implemented that anticipates perturbations in order to reject disturbances. This control has a PI regulator to cancel long-term errors and some of the mid-term cyclic errors. A repetitive regulator is implemented to reject the periodic disturbances that are not totally cancelled by the classical PI control. A filter is added to give robustness against non-periodic disturbances. Implementing a joint PI-repetitive control, we were able to keep the reference weight within ±6 grams (RMS of 3.6 g., about ±1.5% deviation) and to cancel to a large extent the cyclic weight variations. Experimental results indicate that the measurement module and the control system perform satisfactorily, fitting expected quality requirements.

BIBLIOGRAPHY

[1] G. Ter Laak “Continuous Monitoring and Control of the Glass Contribute to Efficiency and High Product Quality”, International Glass Journal, No 93, pp.32-34, (1997).

[2] Richard Pascal and Bill Barron “Gob Temperature Control Improves Glass Forming”, Glass, pp 52-53, (1998).

[3] X. Liu and R. W. Ehrich, "Sub-pixel Edge Location in Binary Images Using Dithering", IEEE Transactions On Pattern Analysis and Machine Intelligence, vol. 17, no. 6, 629-634, June (1995).

[4] Y. Shan and G.W. Boon," Sub-pixel Location of Edges with non-Uniform Blurring: a Finite Closed-Form Approach", Image and Vision Computing 18, 1015-1023, (2000).

[5] L. O'Gorman, "Sub-pixel Precision of Straight-Edged Shapes for Registration and Measurement", IEEE Transactions On Pattern Analysis and Machine Intelligence, vol. 18, no. 7, 746-751, July (1996).

[6] J. Gluckman, "Rectified Catadioptric Stereo Sensors", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 4, no. 2, 224-236, February (2002).

[7] J.S. Weszka, "A Survey of Threshold Selection Techniques", Computer Graphics and Image Processing 7, 259-265, (1978).

[8] R. C. González and R. E. Woods, *Tratamiento Digital de Imágenes*, Addison-Wesley/ Díaz de Santos, U.S.A., (1996).

[9] G. Pajares and J. M. de la Cruz, *Visión por Computador*, Ra-Ma, Madrid, (2001).

[10] H. Rodriguez, J. L. Pons, R. Ceres, "A ZPET-Repetitive Speed Controller for Ultrasonic Motors", IEEE International Conference on Robotics & Automation, 3654-3659, (2000).

[11] Keliang Zhou and Danwei Wang, "Digital Repetitive Learning Controller for Three-Phase CVCF PWM Inverter", IEEE Transactions On Industrial Electronics, vol. 48, no. 4, 820-830. August (2001).

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