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Computational Intelligence for Automated Keg Identification and Deformation Detection

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Abstract - **A machine vision based keg inspection system can allow cost effective keg tracking and preventative maintenance programs to be implemented, leading to substantial savings for breweries with large keg fleets. A robust keg serial number recognition and keg condition assessment process is required to cater for different keg brands and a range of keg ages in the fleet. It has been demonstrated that the proposed image processing methodology, and neural network based number recognition system, successfully located and identified keg serial numbers with a 92% digit accuracy. Furthermore, the vision system allowed the concurrent assessment of the keg condition by assessing deformity of the keg rim, and that of the filler valve. A correlation coefficient, generated using a template matching process, proved to be a suitable metric which adequately indicated rims within and outside acceptable deformity bounds.**

Index Terms – Neural Networks, OCR, Keg Deformation Detection, Keg Tracking.

I. Introduction

For most breweries the modern stainless steel keg has replaced the wooden barrel as the primary transportation and product delivery vessel in the draught beer supply chain. Keg fleet sizes can be in the order of tens of thousands [1] or up to millions [2]. The fleet size is proportional to the size of the brewery, supply chain latencies and the geographic dimensions of its customer distribution network. With the price of a new keg at around USD100 [3], the asset value of a keg fleet is often second only to that of the fixed plant [4]. In theory a modern keg should be physically able to survive for up to 20 or 30 years [5]. In practice, damage, theft and loss all contribute to annual attrition rates of between 5% and 20% [3].

A. Keg Asset Management

A keg asset management system that could reduce the supply chain cycle time of kegs (including through maintenance management) as well as help reduce the annual rate of attrition, would have a strong business case [1][6]. A number of breweries have adopted a range of different strategies to address this issue [7]. Such solutions include a cash-neutral deposit system [8], the use of disposable kegs[1], or outsourcing the management and operation of the entire keg fleet to a third party such as *Trenstar*[2] [9].

For a keg asset management system to address the high annual rate of attrition, it needs to be able to monitor numerous things including the keg's history, cycle time patterns in trade and its most recent destination. In order to do this it requires a means of automatically identifying each keg [10][1][8]. A number of different technologies for automated keg identification have been proposed. Some of the more notable include: bar codes (regular, holographic [8], two-dimensional [5]) and the RFID tag [4][6][11]. However both of these options require modifications to every keg, which is a significant commitment (depending on the type of transponder RFID tags can cost up to USD5[3] each). For the kegs currently in trade, the only way to automatically identify them without modifying each keg is to use machine vision techniques to read each keg's existing unique ID number (that is stamped into the top metal dome). *Syscona*[4] have developed a system that is capable of reading the ID number on the top of brand new kegs. However there exists a greater potential for a machine vision system which can read the ID number, on the processing line, for a large number of kegs already in circulation and in varying condition (aged, weathered, marked).

An automated keg ID system could also form the core of a preventative maintenance system. The financial consequences of damaged kegs can include unnecessary interruption to production, having to replace leaking kegs at a customer's premises as well as the potential safety issues of kegs that cannot stack properly. A real-time automated keg identification system that is coupled to a national keg asset database would underpin the core of a preventative maintenance system. This would enable an asynchronous audit of the keg fleet to be conducted with a simple database query (a task that is currently very expensive, time consuming and labour intensive). Such a system could also display the age distribution and history of the keg fleet. In a real-time sense it could also be used to identify and remove foreign

[1] http://www.ecokeg.com

[2] http://www.trenstar.com

[3] http://www.schaeferkegs.com

[4] http://www.syscona.de

kegs from the production line and for diverting relevant kegs for preventative maintenance.

These estimates and activities are currently based on visual assessments and counts of kegs moving through the plant. Machine vision systems have a relatively long history of use in the packaging industry (pre 1984) [12]. For bottling lines these systems have been used for a range of tasks including: label inspection, 2d bar code inspection for traceability and security, defect detection in bottle necks and inspection of wrap-around sleeves.

In more recent times machine vision has also been applied to bulk beer containers. An interesting example is the use of robot guidance for the automated removal of wooden bungs from barrels [12]. For modern kegs, machine vision systems have been used for the detection of leaking and faulty spears and valves [12]. *MicroDat* offer a "Keg fit for fill" system that provides an automated assessment of the condition of each keg prior to filling. It contains the *Cognex* 'checkpoint' system that can detect a range of defects including: missing or damages spear, Barnes neck deformation, and chime damage [13]. However there is a clear case for a machine vision based system that can reliably identify the existing ID number as well as detect deformations on the millions of weathered kegs circulating in the trade.

This paper presents some initial research which tests the technical feasibility of implementing an on-line keg ID number location and identification schema, coupled with an automatic visual inspection process which provides some indicators of key detectable deformities.

In planning for implementation in the production line, it is assumed that the kegs will pass upright through the ID rig prior to the filling lanes, and that a time interval of one second is available for ID number identification of each keg.

II. Keg Geometry

Each keg has a unique serial number stamped with a defined orientation on the keg dome. Different brands can use different fonts and different orientations. Orientation is often specified as a certain radius from the dome centre and a certain offset from the mid-line. Some keg brands have other inherent landmarks such as spokes embossed into the dome.

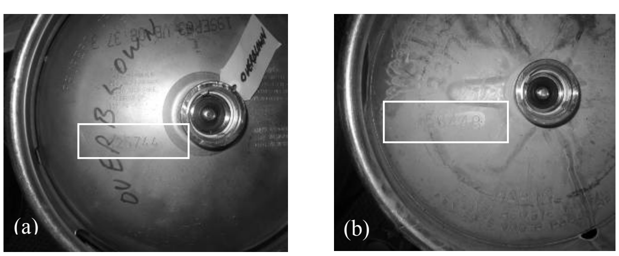


Fig. 1: ID number positioning for two different keg brands: (a) *Blefa* (smooth dome), (b) *Thielmann* (spoked).

The test keg fleet used for this study comprised *Blefa*, *Spartanburg*, *Rheem* and *Thielmann* (the three latter brands have a six spoke pattern on the dome). Fig. 1 illustrates two keg domes of two different brands. The serial number locations are indicated with boxes.

It is not uncommon for the ID numbers to be occluded by foreign substances (dust, dirt, etc), abrasions or corrosion. Sometimes they are not correctly embossed and the digits are difficult to read, even by a skilled operator.

This initial stage of research was performed in a controlled laboratory setting with a sample set of kegs - some with well defined and readable ID numbers, some with occluded ID numbers and some with a range of deformities.

III. Keg ID Number Extraction and Recognition

Lighting configurations, image capture equipment and machine vision techniques were trialed. Machine vision techniques developed for ID number extraction and recognition, and assessment of keg deformity are presented in these two sections.

ID number recognition was performed in a three stage process - image capture and pre-processing (conditioning), number segmentation, and recognition. Fig. 2 maps out all of the steps involved and expands on the pre-processing stage described herein.

A. Image Conditioning

Serial number to dome background contrast is firstly maximized. In part, this is achieved through the use of uniform incidental lighting flooding the entire dome. In consideration of a real-time implementation (deemed to be one second processing time per keg), the dome image is converted to 8-bit grey scale.

A Laplace of Gauss (LoG) operator is then applied to suppress noise and enhance (digit) edges. This process uses the two-dimensional derivatives of the Gauss-function together with a Gaussian low pass filter [14]. The LoG operator computes the Laplacian $\Delta g(x,y)$ given by the kernel expression:

$$\Delta G_{\sigma}(x,y) = \frac{1}{2\pi\sigma^4}\left(\frac{x^2+y^2}{2\sigma^2}-1\right)\left[\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\right] \quad (1)$$

with σ set to a value of 2.

The filtered image is thresholded creating a one-bit deep image plane. A 7.5 pixel radius dilating circle is applied which produces elongated areas corresponding to edges in close proximity (as shown in Fig. 3 (a)). Such areas include sequences of characters including the candidate serial number.

B. Location and Segmentation

Where as some of the geographical ID number location parameters are known for each keg brand, the angular orientation is not precisely known. Likewise, the rotational orientation of the keg is not known on the production line when image capture would occur.

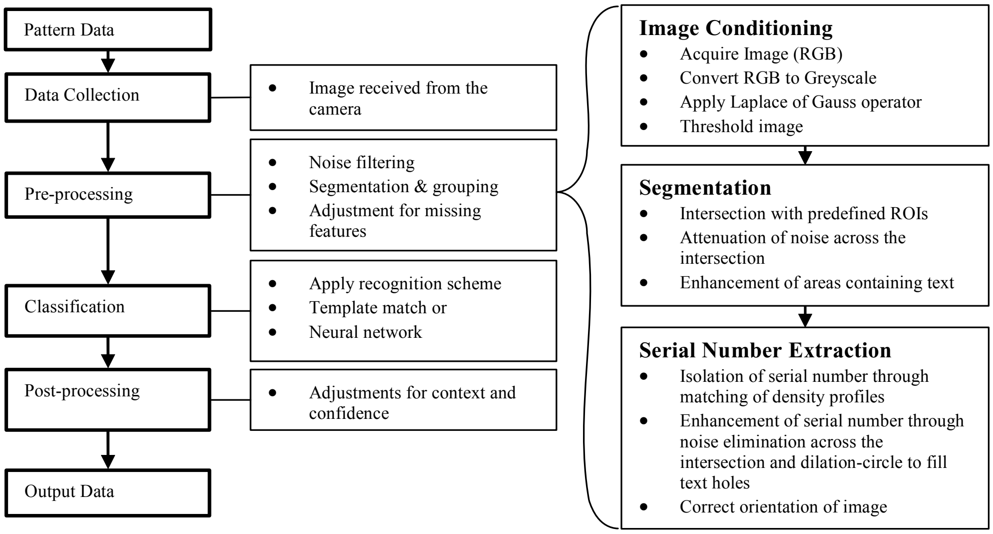


Fig. 2: Image capture, conditioning and serial number recognition process.

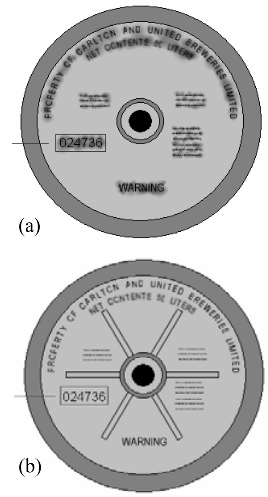


Fig. 3: Auto-location of serial number using (a) density profiles and (b) location of serial number within a spoked segment.

Each brand has defined regions in which ID numbers are located. These regions become regions of interest (ROIs) over which an ID number mask is passed, and a recognition procedure attempted and evaluated as to the existence of a legitimate ID number. These ROIs are defined to have rotational tolerance.

The centrally located filler valve is an easily detectable reference point for the centre of the keg dome. The region(s) of interest are therefore defined with respect to the filler valve and are defined in terms of radii from the origin as defined by each brand. Any relatively small translational shift within a conveyor line is offset through the automated location of the filler valve.

The mask is digitally rotated about the centre of the keg at radii corresponding to the defined ROIs. Candidate ID numbers are indicated by the return of a high density set of pixels (resulting from the dilating circle procedure) coinciding with the mask location. It was shown that this process generally demonstrated a distinguishable pattern corresponding to an ID number location. However, it was noted that a section of rust/scratches could return a false positive for candidate serial number selection. Such occurrences are most likely to involve localised regions of the dome rather than the whole dome. Regions that do return false positives, must then successfully undergo positive digit recognition and then, further, have the number authenticated against an intelligent database.

Given the unknown rotational orientation of the keg, some keg brands require an iterative stepping of the mask around the origin to locate candidate ID numbers. This is the case for the *Blefa* brand of kegs. With no other geographical features which would allow the refinement of locating the ID number, the mask is exhaustively stepped around at increments of 2.5° around the ROI until a true-positive is detected.

Conversely, the *Spartanburg*, *Rheem* and *Thielmann* brands of kegs have a spoked pattern embossed on the dome. By identifying the spokes (six in these instances), the serial number is relatively simply located as it is stamped within a relatively concise location with respect to the spokes. It therefore requires only six discrete rotational steps of the mask to find candidate ID numbers.

The spoke detection process can therefore be used as a screening process which indicates whether the dome is spoked or unspoked (and therefore *Spartanburg*, *Rheem* and *Thielmann*, or *Blefa* respectively) and the appropriate stepping algorithm, with respective ROIs, engaged to locate the ID number.

A further qualification to this algorithm is that it is possible for kegs to be overblown. Overblowing results from an action that pressurises the keg and pushes the dome out. For example, a keg full of beer may be inadvertently frozen and thereby stretches the keg as the contents expand. This has the effect of (a) increasing the height of the dome, and (b) reducing the depth of any spoke embossing. Therefore, the algorithm allows for the fact that an apparently unspoked dome may be a *Blefa* keg, or it may be an overblown keg. A process that may detect heightened, and therefore stretched, domes is discussed in a following section.

Following one complete rotation of a mask, whether following the spoked or unspoked stepping procedure, a negative serial number (or numerous candidate ID number) detection suggests that there is poor discrimination of digits from the background. This may be either due to extreme damage such as widespread abrasions, foreign substances coating the dome such as paint, or the keg may be overblown. In all of these instances, intervention is required and the keg can then be removed from the production line for repair or decommissioning.

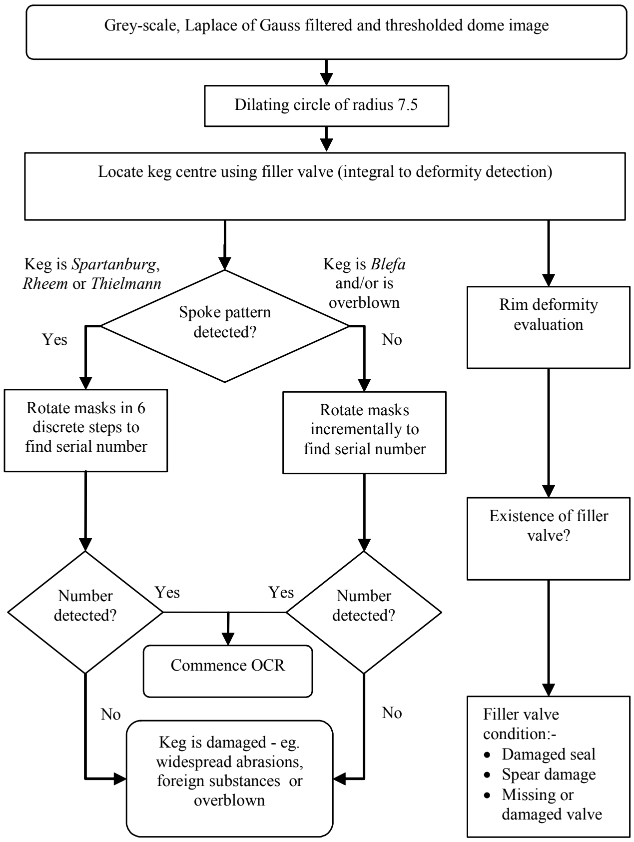


Fig. 4: Flow chart of serial number detection and extraction, and deformity detection.

The flow diagram of this process, and depiction of the flow onto the digit recognition process is shown in Fig. 4. A further consequence of this whole procedure is that it is a relatively simple process to check for any physical deformities from the perspective of an image captured of the keg top.

IV. DIGIT RECOGNITION

Both template matching and neural networks were trialed to classify digits within candidate ID numbers. The results of this trial are summarised below. A greater discussion can be found in [15].

A. Template Matching

A series of templates was created representing each digit formed as a hybrid from the font set of the different brands of kegs. These hybrid digit templates were used as references for template matching whereby the degree of coincidence (the total sum of differences) between the candidate digit and each of the templates is returned. This metric is used to determine the degree of match with each template and is then used to determine the greatest match.

A test based on a sample of the newer *Blefa* kegs (chosen for the reduced occurrences of blemishes and damage) resulted in a less than acceptable 72% recognition rate (true positives). Be that as it may, it was found that the poor recognition rate was still influenced by three factors.

1. Some digits were poorly stamped in the first instance and would defy human visual interpretation. Alternatively, some digits were occluded by markings which, in all, could also reasonably lead to human misinterpretation.
2. The template matching methodology requires candidate digits to be delineated by clear space. In some instances, extraneous pixels eliminated any clear space between digits, thereby rendering two digits being misinterpreted as one, and thereby misclassified.
3. Extraneous pixels with clear space on either side were interpreted as being candidate digits, and in some instances falsely interpreted as valid digits, albeit with a low confidence level.

Further tuning of the image pre-processing methodology as well as the implementation of predefined inter-digit spacing would contribute to improving the performance of template matching. However there still exists the inherent sensitivity to digit translational and rotational shifts.

B. Neural Network

An alternative approach to the template matching schema is learning-based, computationally intelligent methods trained with data tolerant of translational and rotational variation (within limits). In this first instance, neural networks were trialed for recognizing keg ID numbers.

A three layer feed-forward neural network (one input layer, one hidden layer and one output layer) was used [15]. The number of input layer nodes corresponds to the number of pixels in the scanning pixel array. The number of output neurons corresponds to the number of output classes (digits). The number of hidden layers, and the number of neurons within each layer is ultimately governed by the objectives of forming generalized solutions (as opposed to forming particularized solutions), and achieving acceptably high performance. In this instance, it was found that a single hidden layer with 32 neurons was sufficient to achieve the results described below.

A 60 x 100 pixel block is used to scan the candidate ID number. This pixel block is connected directly to the 6000 input layer (one input node per pixel). At any given time, the data presented to the input block is assessed in terms of the strongest digit class beyond an acceptable threshold. The output layer comprises 10 neurons corresponding to the 10 digit classes. A log-Sigmoid function was used for the neuronal activation function.

The neural network was trained as described in the two following steps.

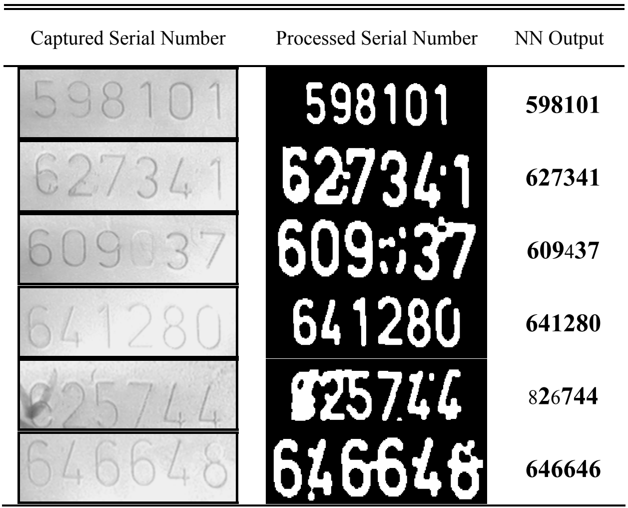


Fig. 5: Serial number examples and return values. From top: a) SN589101, b) SN627341, c) SN609037, d) SN641280, e) SN625744 and f) SN646648.

1. A set of idealised exemplars was constructed and used to train the network until it reached the predefined sum-squared error goal of 0.1.
2. The exemplars were then augmented with random noise (0.1 and 0.2 standard deviations to the idealised training vector). This assisted with the generalisation process.

Examples of the *Blefa* training exemplars for the digit "3" are shown below in Fig. 6.

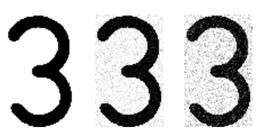


Fig. 6: Training vectors with application of random noise with standard deviation of (left to right) 0, 0.1 and 0.2.

Overall, the neural network achieved an improved recognition rate of 92%. No classifications were made for non-existing digits and 8% of existing digits were incorrectly classified. Fig. 5 shows examples of original serial number images, pre-processed candidate serial numbers and the corresponding neural network based digit classifications.

As with the template matching trial, the results were affected by digits which were malformed in the stamping process (3rd serial number in Fig. 5), and those occluded by dirt and markings (5th serial number in Fig. 5). In consideration of the visually difficult digits by humans, the misclassification rate of digits otherwise well-formed and easily identified by humans (5th serial number in Fig. 5) was found to be 3%.

In summary, the results for the serial number digit recognition trial of template matching and neural network are given in Table 1. False positives are those cases for which a digit was classified and either it did not exist or it did exist but was incorrectly classified. False negatives are those cases where a valid digit was not recognized at all.

It is accepted that both methods could be improved with greater a-priori knowledge of the keg fonts and style, and with cleaning procedures implemented in the keg conveyer line – such as caustic washing to remove extraneous marks.

TABLE I
RECOGNITION RATES OF TEMPLATE MATCHING AND NEURAL NETWORK BASED OCR

	TEMPLATE MATCHING	NEURAL NETWORK
True recognition	81%	92%
False Positives	25%	8%
False Negatives	3%	0%

However, it was shown that the neural network approach did out perform the template matching approach in terms of translational and rotational shifts which cannot necessarily be avoided in a factory implementation.

V. DEFORMATION DETECTION

Another advantage of using a machine vision based system for the purpose of asset tracking, is that the system may also be used to aid in the maintenance of individual assets (kegs). To this end, some preliminary investigation was performed with regard to deformation detection of the keg structure. Two key areas for distortion were examined – deformation of the keg rim (leading to issues pertaining to the stacking of kegs), and also deformation of the filler valve and surrounding area (leading to leakage and poor sealing of the product).

Damaged keg rims are indicative of mishandling and can indicate further damage resulting in potential product loss and a stacking risk. Image capture of the entire keg dome and rim, and locating the dome centre (as is required for the ID number location), provides a mechanism to detect some key faults and deformities without significant incremental computational burden. The basic premise behind model (or shape) based deformation detection is the comparison of an ideal image with that taken of the object being investigated, and the subsequent action based on the degree of correspondence between the two. In both cases, a synthetic model was created which was then applied to a captured image of the keg dome.

A. Keg Rim

A generic template for the keg rim was synthesized corresponding to the *Spartanburg*, *Rheem* and *Thielmann* kegs. It was ensured that the correlation coefficient between the synthetic rim template and all undistorted keg rims in the test fleet was > 0.95. This template was then applied to kegs with differing degrees of deformation to the rim.

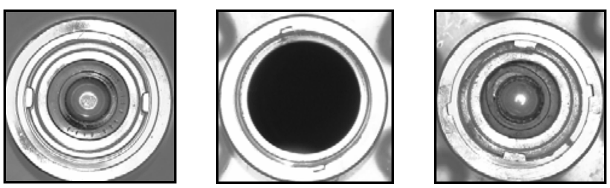
It was found that kegs showing signs of some deformation yet deemed servicable, returned correlation coefficients of ≥ 0.51. A *Blefa* keg with a rim in good condition is shown in Fig. 7(a). A *Spartanburg* keg which had a significantly damaged rim, and clearly unserviceable, is shown in Fig. 7(b). It returned a correlation coefficient of approximately 0.3.

A value of 0.50 was adopted as the preliminary lower boundary of the pass threshold for keg rim deformity. It is expected that this value would be refined when applied to a more extensive fleet of test kegs.

Fig. 7: (a) Ideal keg rim shape – *Blefa*, (b) Damaged *Spartanburg* keg.

B. Filler Valve

In a similar manner to the keg rim deformation detection, a synthetic model of the filler valve seal was created and then used to test for its presence and key characteristics within the keg image. Sample images illustrating the filler valve, and key variations are shown in Fig. 8.



(a) (b) (c)

Fig. 8: Variations in filler valve assembly. (a) Filler valve assembly in good order, (b) Neck spear missing from the filler valve assembly, and (c) Damaged filler valve seal.

Initially, the presence of the filler valve was tested for (a binary result) returning 100% correct values in the test set. Ultimately, this procedure could be developed to locate and examine other areas of interest within the filler valve assembly – detection of the presence of the circlip, crazing/cracking of the filler valve seal, and damage to the neck spear.

VI. Conclusion

The preliminary results presented in this study demonstrate that machine vision based keg serial number recognition and keg deformity detection is a viable methodology as a component of an asset management system for large beer keg fleets. The machine vision approach is preferred as there is no capital investment required on the keg fleet itself, which could amount to millions of dollars (USD) for large fleets. The potential technical merits of the machine vision techniques investigated in this study indicate that such an approach may be feasible in terms of a business case. The resulting capital investment would primarily be in production line keg handling processes, a sophisticated illumination and image capture configuration system, computational processing capability (not seen to be a major issue within the context of that already available in the plant), and the underlying integration into corporate databases and reporting systems.

This study has demonstrated the feasibility of machine vision keg serial number location and digit recognition for a variety of keg brands in a variety of conditions. An initial neural network digit recognition rate of 92% was achieved. This figure does need to be improved to ultimately achieve the target of 98% through further tuning of the image processing methods and the possible adoption of hybrid neuro-fuzzy based recognition.

Keg rim deformation was assessed using a synthesized generic template representing an ideal keg rim suitable for all keg brands in the test set. The application of a template matching scheme, and resultant correlation coefficient, indicated that those kegs returning correlation coefficients of ≥ 0.50 have rims which are in acceptable condition. Those below this value have unacceptable rims and should be removed from circulation for preventative maintenance or decommissioning.

Keg filler valve detection was also demonstrated through the application of a synthesized template. There is the potential to extend this methodology to detect the existence, and condition of, the components within the filler valve.

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