COVER SHEET

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NEURAL NETWORK BASED OCR FOR KEG IDENTIFICATION

Andrew Keir [1], Michael Lees[2], Duncan Campbell[1]
[1]School of Engineering Systems, Queensland University of Technology
[2] Foster's Australia, Yatala Operations, Beenleigh
Australia
da.campbell@qut.edu.au

ABSTRACT
A keg asset management system that can reduce the annual rate of keg attrition by 5% to 20% can deliver significant savings to breweries with large fleets of kegs. A typically large brewery can have at least tens of thousands of kegs, a sizable investment given an initial cost of around USD100 per keg. A key element in a keg tracking system is on-line keg identification. This research explores the feasibility of an intelligent machine vision approach to identifying the unique serial number embossed on the dome of each keg at manufacture. The demonstration system developed auto-locates candidate serial numbers and applies optical character recognition (OCR) techniques. The neural network based OCR achieved the best performance over template matching achieving an overall recognition rate of 92% and no missed digits. If non-permanent serial number occlusions can be removed by caustic washing prior to the image capture stage in a production line implementation, the recognition rate approaches 97%.

KEY WORDS
Neural networks, OCR, keg tracking

1. Introduction

The modern stainless steel keg is the key transportation and product delivery vessel in the draught beer supply chain. Each keg costs around USD100 each when new [1]. The number of kegs that a brewery requires to cater for keg losses and cycle times at various points in the supply chain is estimated to be up to eight in support of each pouring tap [1]. The size of a keg fleet can range from tens of thousands [2] to millions [3] depending on both the size of the brewery and the characteristics of its customer distribution network. With these figures, the asset value of a keg fleet can be very high, even to the point of being second only to that of the fixed plant [4]. Theoretically kegs are able to survive upward of 20 to 30 years [5]. However the real financial burden of maintaining a keg fleet becomes apparent when the annual rate of attrition (including loss and theft) is considered. This can range between 5% and 20% depending on location [1]. Hence there is a clear business case for a keg asset management system that can help to reduce the annual rate of attrition and supply chain cycle time.

Keg Asset Management

The primary driver for finding better ways to manage the keg fleet is that of cost. Most of the costs incurred relate to the returnable nature of the kegs, or more specifically kegs either not being returned on time or not being returned at all. A number of different strategies have been proposed to address this issue. In the United Kingdom, a cash-neutral deposit scheme has been introduced providing a direct financial incentive for the brewery's customers to return the kegs on time [6]. Another option is for the brewery to outsource their entire keg fleet to a third party to manage such as *Trenstar*[1] [7]. This approach doesn't address the issue, it just transfers the challenges of keg asset management to a third party. The fact that these issues don't exist with packaged beer (cans and bottles) has also led to concept of the non-returnable keg. Advanced materials and clever design have resulted in a relatively cheap disposable keg[2] that is effectively sold to the customer with the beer [7].

Due to the strong business case, the concept of automated keg identification and tracking has become increasingly popular in recent times [2][8]. An automated keg identification system that is coupled to a national keg asset database would underpin one solution to the keg asset management problem. A real-time automated system could be used to identify and remove foreign kegs from the production line and for diverting kegs for preventative maintenance.

Techniques for Automated Keg Identification

At the heart of a keg asset management system there needs to be an automated means of identifying each keg [9]. A range of different technologies has been proposed for this function. The simplest of these is the regular bar code. Extensions on the bar code concept include a holographic bar code [6] (for improved authentication) or a laser etched two-dimensional bar code [5] with improved resilience to occlusion. However the most

[1] www.trenstar.com
[2] www.ecokeg.com

popular option in use today (including by third party keg fleet management companies such as *Trenstar*) would be the RFID tag [4][8][10]. The fundamental drawback of both the bar code and RFID tag techniques is that they require each and every keg to be modified. Given the typical fleet size this can be a significant cost, particularly considering that RFID tags can cost up to USD5[3] each (depending on the type of transponder).

An alternative approach is to use machine vision techniques to read the unique ID number that is stamped into the metal dome on the top of each keg. *Syscona*[4] have developed a system that is capable of reading the ID number on the top of brand new kegs. Customs, in some countries, require a human readable but automated means of verifying the keg's RFID tag. However there is still a much larger market for a machine vision system that can reliably read the ID number on the high volume of aged and weathered kegs in circulation. The most significant benefit of a machine vision based solution is that it does not require costly alterations to each and every keg.

2. Keg Characteristics & Constraints

There are four different brands within the keg fleet of interest: *Spartanburg*, *Rheem* and *Thielmann* (all of which have a spoked pattern on the dome), and *Blefa* (which does not have a spoked pattern). These differences are illustrated in the example shown in Figure 1.

The kegs have the following relevant properties:-

- A unique ID number stamped on the top dome
- ID number orientation is consistent within each brand
- Different brands use different fonts and have different orientations
- ID numbers are subject to occlusion by foreign substances (dust, dirt, etc.) or even partial corrosion

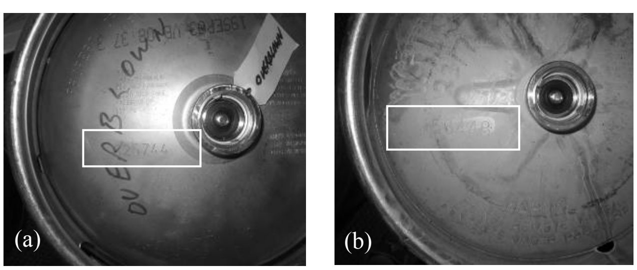

Figure 1. ID number positioning for two different keg brands: a) Blefa (smooth dome), b) Thielmann (spoked)

The first stage of research was conducted off-line in a laboratory using a sample collection of kegs. The controlled environment enabled the tuning of lighting configurations, image capture equipment and the development and testing of machine vision techniques. 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.

3. Keg ID Number Extraction

An image-based keg serial number recognition method was developed based on image capture, pre-processing (conditioning), number segmentation and recognition. The particular steps in this approach are mapped out in Figure 2. This section discusses the pre-processing involved to locate and extract the candidate serial number. The following section presents the outcomes of two methods examined for digit recognition – template matching and neural networks.

3.1 Image Conditioning

Each image is treated to maximise the serial number contrast to the dome background. In part, this is achieved through the use of uniform incidental lighting flooding the entire dome. The dome can be of varying sheen, it can be corroded or it can have occluding marks. It is proposed that image capture occurs after the external caustic wash to minimise the effects of such. However there remains some finite potential for these effects to have some influence.

Ultimate implementation in real-time (one second per keg) is a consideration and therefore the first step is to convert the image to grey scale to reduce the bit-depth.

The image undergoes an edge enhancement and noise suppression process through a Laplace of Gauss (LoG) operator ($\sigma = 2$). This filter uses the two-dimensional derivatives of the Gauss-function together with a Gaussian low pass filter for noise suppression [11]. The LoG operator computes the Laplacian $\Delta g(x,y)$ given by the kernel expression:

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

Edges are defined by zero-crossings of the filtered image. This operator tends to be insensitive to noise and provides faithful representation of edge positions even with low-edge gradients [12][13].

3.2 Location and Segmentation

The filtered image is thresholded and represented by a one-bit deep image plan. A dilating circle is applied with a radius of 7.5 pixels was chosen such that a sequence of numbers appears a single elongated area facilitating the serial number location process as illustrated in Figure 3a.

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3 www.schaeferkegs.com

4 www.syscona.de

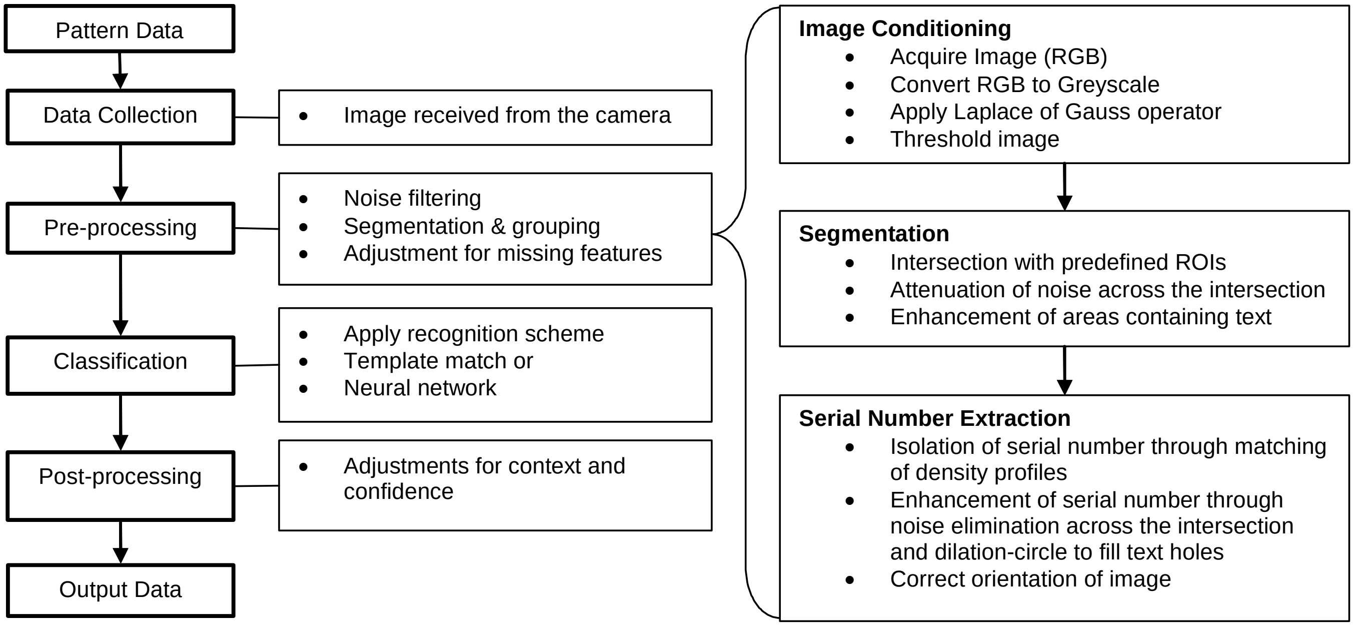

Figure 2: Image capture, conditioning and serial number recognition process

The rotational aspect of the keg is not known during image capture, therefore candidate serial numbers are required to be detected with rotational independence. The keg fleet of interest has known geometrical characteristics within each brand. Broadly speaking, the four brands are grouped into spoked (*Spartanburg*, *Rheem*, *Thielmann*) and unspoked (*Blefa*) domes as shown in Figure 3.

These characteristics lend themselves to the application of a serial number mask which is passed over legal locations on the dome corresponding to each keg brand. Each brand dictates valid regions of interest over which the mask is applied and candidate serial numbers detected.

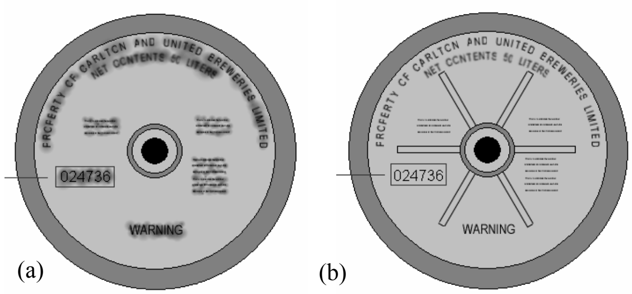

Figure 3: Auto-location of serial number using a) density profiles and b) location of serial number within a spoked segment

The region of interest is defined by the easily locatable filler valve. Each brand then has an annular locus of serial number candidate locations. This approach effectively addresses any translational shift of the image from true centre along the longitudinal axis within the context of a conveyer line.

The mask is digitally rotated about the keg centre point, as defined by the centre of the filler valve. As the mask passes over the broadened serial number, the higher density collection of pixels is detected. Analysis of the size of the text present on the dome of the keg showed that the serial number would return a clearly distinguishable pattern quite unlike that of any of the other areas.[5]

The manner in which the mask is rotated depends on whether the dome is spoked or unspoked. *Spartanburg*, *Rheem* and *Thielmann* brands have the serial number stamped consistently in relation to the six armed spokes. The spoke pattern is easily distinguishable and is used as a landmark for six discrete rotational steps of the mask. The serial number must appear within one of the six segments contained within the arms of the spokes (see Figure 3b). This decreases the number of rotational steps required to locate the serial number. This process can be used as a first pass stage for image rotation and serial number detection. Should the spoke pattern not be detected, the keg is either a *Blefa* or it is overblown.[6]

A *Blefa* keg does not have the spoked pattern as a convenient landmark. Rather than the serial number mask being rotated in six discrete steps (coinciding with the six candidate locations of the spokes), it is incrementally rotated at relatively small angles (eg. 2.5°). The serial number is then detected as the high density region of pixels passes through the mask region.

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[5] It is noted that a section of rust/scratches could return a false positive for the serial number section. Whilst requiring further investigation to exclude such an occurrence from interfering with the data, the likelihood of such a section being contained to a small area and not enveloping the whole of the keg dome would be quite small.

[6] If a full keg is placed in a cellar that is so cold that the beer freezes, it will expand and stretch the actual keg. This stretching almost always results in an increase in the height of the top dome of the keg.

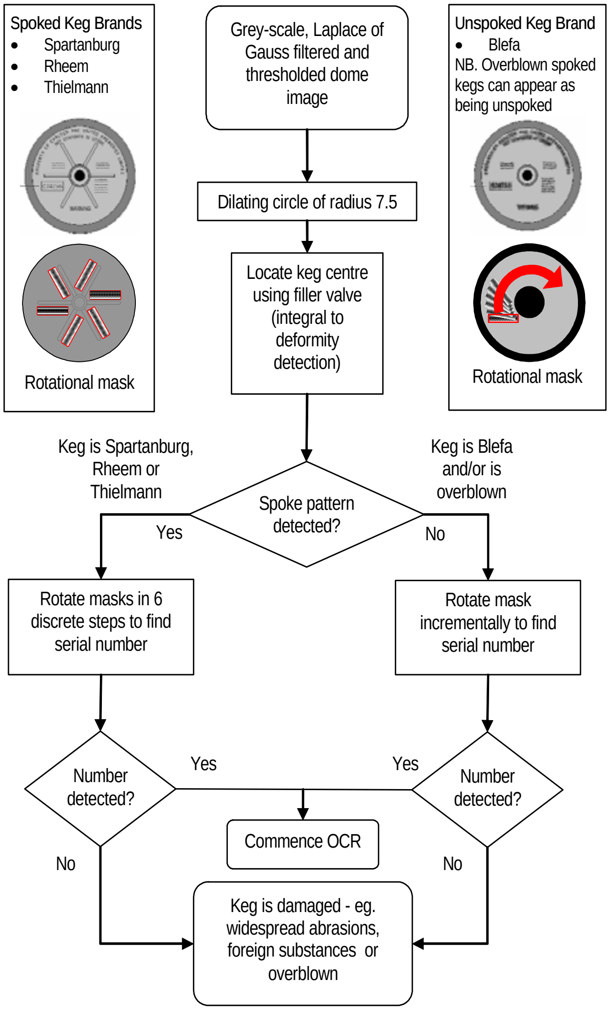


Figure 4: Flow chart of serial number detection and extraction

Following one complete rotation of a mask, a negative serial number detection suggests poor discrimination of digits from the background. This can 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 these instances, intervention is required and can be flagged. The keg can then be removed from the production line for repair or decommissioning.

The positive detection of a candidate serial number is submitted to optical character recognition. The flow of operations and decisions is summarised in Figure 4.

4. Digit Recognition

Two methods were investigated to classify serial number digits using optical character recognition methods. One is based on template matching and one using neural networks.

4.1 Template Matching

The adopted OCR template matching approach was to match the input pattern image to an artificially created template. Font tolerance was catered for through appropriate template design, with the degree of coincidence (or the total sum of differences) between the pattern and the template given a metric by which a specific character could be identified.

An artificial template was created and applied to the newest set of kegs (*Blefa*) so as to determine the accuracy of the template matching approach with minimal impact from variations in sheen, scratches and surface damage.

Table 1. Experimental recognition rates of template matching based OCR

Overall true recognition rate	72%
False positives[7]	25%
False negatives[8]	3%

As can be seen in Table 1, template matching based recognition achieved a 72% overall successful recognition rate – an unsatisfactory result. This recognition performance appears to be strongly related to three factors:

1. Visually malformed digits that would challenge human visual inspection. This includes instances of poor embossing (stamping) of the digit (Figure 6c), and markings occluding digits (Figure 6e). The former instance will always provide a challenge. The latter instance can in part be dealt with through caustic cleaning of the keg prior to inspection.
2. The digit registration method to delineate digits relied on the existence of clear space between digits. There were instances where extraneous pixels (by-products of the pre-processing) effectively joined adjacent digits and thereby eliminated the required inter-digit spacing. Some further tuning of the pre-processing stage as well as using predefined digit pitch spacing may assist in improving the false classifications.
3. Extraneous pixels with space on either side were taken as being candidate digits and are therefore expressed as false positives.

The nature of the keg serial number identification problem has inherent translation and rotation variation. Since template matching relies heavily on spatial correlation (or coincidence) it is therefore very sensitive to these variations.

4.2 Neural Network

It is proposed that sensitivity to translational and rotational variation in candidate serial number location and orientation can be reduced through the use of learning

[7] Those cases for which a digit was classified and either it did not exist or it did exist but was incorrectly classified

[8] Those cases where a valid digit was not recognized at all

based computationally intelligent (CI) methods trained accordingly. Candidate CI methods include neural networks and hybrid neuro-fuzzy systems. Neural networks were examined as an initial solution to keg serial number OCR.

A three layer feed-forward neural network (one input layer, one hidden layer and one output layer) was used [14]. 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 main consideration in selecting the number of hidden layers and the number of hidden neurons is that of having sufficient neurons to achieve acceptable performance whilst maintaining generalisation within the solutions. It was found that a single hidden layer was sufficient to achieve the results described below.

The neural network was based on input data obtained from a scanning 60 x 100 pixel block. At any given time, the data presented to the input block is assessed in terms of the strongest digit class. The neural network therefore has 6000 input neurons (corresponding to the pixel block), 10 output neurons, to identify the ten digits in each font, and a single hidden layer of 32 neurons. The activation function for all neurons is a log-Sigmoid function.

A set of training digits was constructed corresponding to the size of the input block and the network trained with the following two steps.

1. A set of idealised data vectors was used to train the network until it reached the predefined sum-squared error goal of 0.1.
2. The vectors were then augmented with random noise (0.1 and 0.2 standard deviations to the idealised vector) in order to assist with the generalisation process and facilitation of correct digit identification (noisy as well as clean).

Examples of the *Blefa* training exemplars for the digit “5” are shown below in Figure 5.

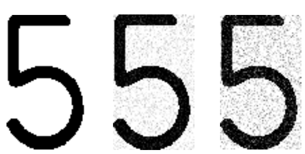


Figure 5: Training vectors with application of random noise with standard deviation of (left to right) 0, 0.1 and 0.2

Figure 6 below shows examples of original images of serial numbers, pre-processed candidate serial numbers and the corresponding neural nework based digit classifications. The examples include a digit which was poorly embossed (c) and misclassified, and one digit which was occluded by a marking and misclassified (e).

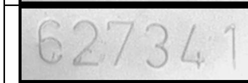
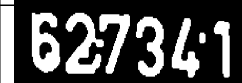
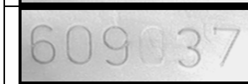
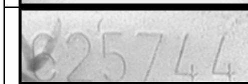
Captured Serial Number	Processed Serial Number	NN Output
		598101
		627341
		609437
		641280
		826744
		646648

Figure 6: Serial number examples and return values. From top: a) SN598101, b) SN627341, c) SN609037, d) SN641280, e) SN625744 and f) SN646648

The digit recognition results are summarised in Table 2 below.

Table 2. Experimental recognition rates of neural network based OCR

Overall true recognition rate	92%
False Positives	8%
False Negatives	0%

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. Taking into consideration those digits which were malformed in the stamping process, and those occluded by dirt and markings (as cited above in the template matching case), presenting significant challenges for human visual inspection, a recognition rate of 97% is arguable.

5. Conclusion

A business case supporting machine vision based keg serial number recognition is being considered in order to automate the tracking of large beer keg fleets. The machine vision approach is preferred as modification is not required of each and every keg. The challenge is to ultimately achieve a recognition rate of at least 98%, in real-time (one second per keg) in what can be challenging conditions in terms of the visual condition of the keg dome.

The envisaged scenario within a production line context is for the kegs to be flipped vertically (following the external caustic wash), passed through a race with appropriate illumination and image capture facilities.

Each image is pre-processed in greyscale with edge enhancement and noise reduction filtering. Regions of interest are scanned with a mask to identify candidate serial numbers. These regions of interest vary from keg brand to keg brand, however the number of brands in a typical fleet is small (four in this instance). A brand dependent catalogue of ROIs can easily be implemented. Spoked keg domes have the advantage of simplifying this process given this added landmark which can be used in locating candidate serial numbers.

Having located a candidate serial number, two methods of digit recognition were examined, template matching and neural network. Template matching produced an inadequate result (72% correct recognition rate) and demonstrated high susceptibility to translational and rotational variations in serial number orientation. Given that this scenario is highly likely in a production line sense, a neural network approach was trialled as an alternative approach. A three-layered feed forward neural network was configured and trained using a library of example digits with noise added for robustness. The resulting network achieved a 92% recognition rate and had no false negatives. It was recognised that a number of digits (around 5%) in the test kegs used would prove to be challenging even for a human operator as the numerals were either poorly embossed, or they were occluded with a mark. Eliminating these particular cases yielded a recognition rate of 97%. This figure is approaching the required level for potential adoption, however consideration will have to be made of these visually challenging instances as they are real. Some can be dealt with through caustic cleaning; some are permanent artifacts within the serial number.

Possible improvements to the recognition rate come through further tuning of the image pre-processing and the neural network recognition stages. Neuro-fuzzy techniques offer potential for improvement as they also embody knowledge aspects of the process.

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