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A machine vision system for the calibration of digital thermometers

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Abstract

Automation is a key point in many industrial tasks such as calibration and metrology. In this context, machine vision has shown to be a useful tool for automation support, especially when there is no other option available. A system for the calibration of portable measurement devices has been developed. The system uses machine vision to obtain the numerical values shown by displays. A new approach based on human perception of digits, which works in parallel with other more classical classifiers, has been created. The results show the benefits of the system in terms of its usability and robustness, obtaining a success rate higher than 99% in display recognition. The system saves time and effort, and offers the possibility of scheduling calibration tasks without excessive attention by the laboratory technicians.

Keywords: metrology, machine vision, calibration, thermometer, automation

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Automation in calibration processes offers a great number of advantages as in speed, in accuracy or in decreasing the error rate [1]. Optimization of these processes is a very important task and, in this field, machine vision systems play a fundamental role [2–4]. In the daily work of a metrology laboratory many instruments need to be periodically inspected at the times required by a calibration protocol. Writing down these measurements is often done manually by the lab technicians. Such a procedure requires full-time work and leads to undesirable delays in calibration in many cases. To make this routine work easier, a machine vision system was developed.

Optical character recognition (OCR) is a pattern recognition problem which has been studied for over 60 years. Multiple classifiers and classification schemes, feature extraction methods, etc have been developed for countless applications in many fields. One can find a lot of literature on these issues from different perspectives [5]. Commercial OCR packages are also available, but most are mainly oriented to document reading and interpretation (not real world scenes). In these applications there are requirements in the capture, illumination, positioning, etc which we cannot achieve, due to the restrictive environment of the calibration process. We have tried GOCR, an OCR program developed under GNU license (www.jocr.sourceforge.net), without success (10% recognition rate). There are also other tools available such as machine vision interfaces or expert systems similar to automatic car-plate recognition systems, which are capable of working under difficult capture conditions. However, these kinds of OCR are designed to work with a previous known format for the digit representation.

There is also some related work dealing with the instrument-reading problem [6], but it focuses merely on a previous known single font display (usually seven-segment).

Figure 1. Some samples of instruments.

However, common instruments have multiple different fonts and may have defects such as scratches or bubbles due to their use in industrial environments, which increases the variance of characters and makes a correct reading more difficult. Our goal is to develop a sufficiently reliable system able to read almost any display without any non-obvious previous assumption about its font type.

The work has been developed for supporting and improving the calibration processes of the Temperature and Humidity Department of the 'Laboratorio Oficial de Metroloxía de Galicia, LOMG' (Spain). In this application, the instruments under calibration are mainly portable thermometers and hygrometers (see figure 1).

The paper is organized as follows. Section 2 provides a system overview. Then, section 3 shows the image processing algorithms. Finally, some results and discussion are presented.

2. System overview

A temperature calibration process establishes the comparison between the measurements obtained by a pattern thermometer and a measurand thermometer under controlled environmental conditions (provided by devices such as baths, climatic chambers, etc). This procedure ensures the traceability of the measurement in the standard definition of Kelvin.

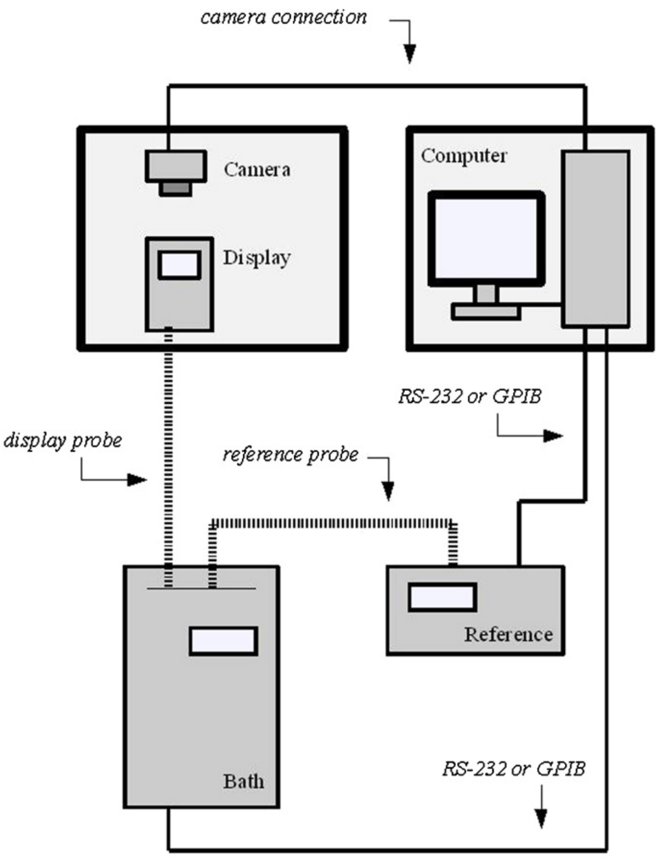

Figure 2. Scheme of a thermometer calibration system.

Calibrations in the Temperature and Humidity Department had been partially automated using the commercial software provided by the pattern devices and the baths for their management (through RS-232 and GPIB ports). Nevertheless, to achieve a better level of automation, we should communicate not only with the pattern devices and baths but also with the measurands. The problem arises that most of the instruments do not have a communication port and there is no standard protocol for this purpose in the remaining ones. Under these conditions, machine vision becomes a key factor for reading and automation.

In most cases measurands have an LCD display where the measurements are shown. The idea is to automatically obtain images of these instruments, extract the numerical values that are shown on the displays and communicate with pattern devices and baths when the protocol requires it. A schematic view is shown in figure 2.

We achieved the best results with a C-Cam BCi4 CMOS (C-Cam Tech.: www.c-cam.be) camera at 1280 × 1024 resolution. A 16 mm lens has shown to be enough to cover the field of view of a typical display at a close distance (20–25 cm). However, a standard 640 × 480 webcam can be used, accepting a decrease in the correct recognition rate. A comparison between the two camera systems is shown in section 4.

Another important improvement of the system, compared to the manual procedure, is the possibility to program a sequence of steps for different temperature ranges in the

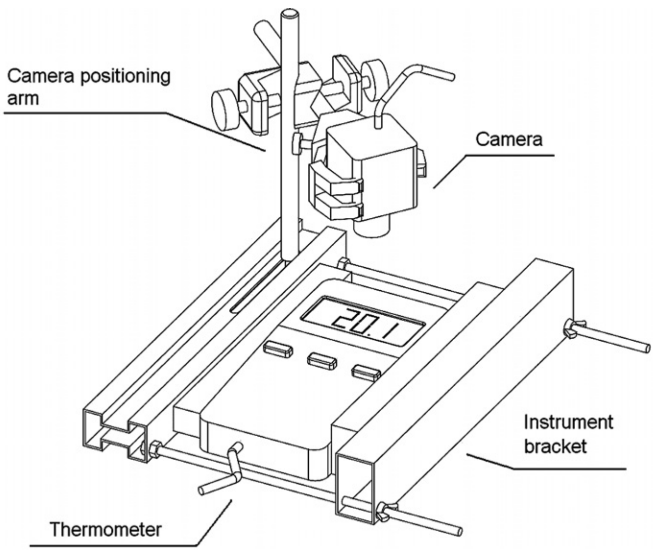

Figure 3. Mechanical mounting.

calibration baths, so that the system can be scheduled to work for 24 h a day without supervision. A manual calibration process of thermometers is long and tedious; with this improvement, the efficiency in the laboratory has increased significantly.

In addition, an assembly (figure 3) has been designed to fix the camera–thermometer system, so that it is possible to move the measurand from one bath to another with no additional re-configurations.

Before starting a calibration process, it is necessary to provide the system with some information relative to the devices to be calibrated, protocols to be followed, etc. The area where the display is located on an image must be found only once, because the setup camera device is fixed. Currently, we still rely on the user to select the region where the display is located. The graphical user interface (GUI) developed to allow these functions is shown in figure 4.

The user can define more than one region of interest (ROI), a useful feature in the case of instruments which have several indications in their displays, or in the case that several instruments can be calibrated in one experiment. The latter happens, for instance, with thermohygrometers, where two values, namely the temperature and the relative humidity, are read. Other parameters of the camera such as the capture period are also selected in this initial phase.

3. Image processing

The ROI extracted by the user is analyzed with standard image processing techniques as described in some detail next. We have enhanced our system with a hybrid recognizer scheme, which combines the use of a classical distance classifier with a new recognizer based on simple human feature perception.

The recognition process starts with the binarization of the image. To avoid problems in images with important illumination gradients, we have designed a multistep procedure. To separate background and foreground in the ROI, a method based on searching the histogram peaks and locating thresholds on the minima between them is used [7]. This method is only effective in the case of bimodal histograms, so if there are more than two prominent peaks, the algorithm switches to an alternative method. First, the threshold quality is estimated with the measurement of the area in the threshold boundary (figure 5). This value is an indicator of the separability of the peaks in a bimodal histogram. If the area exceeds 2.5% of the entire histogram, we switch to a threshold algorithm based on interpolation [8] with a 4×3 sub-image grid which uses the Otsu threshold on each piece which is implemented via an approximate iterative version [9, 10]. The overall procedure is summarized in figure 6.

Then, other typical preprocessing techniques, including filters to reduce noise or skew angle correction (figure 7), are applied to enhance the image before the segmentation process starts. Character row extraction is also applied taking

Figure 4. System GUI (region of interest is marked with a rectangle).

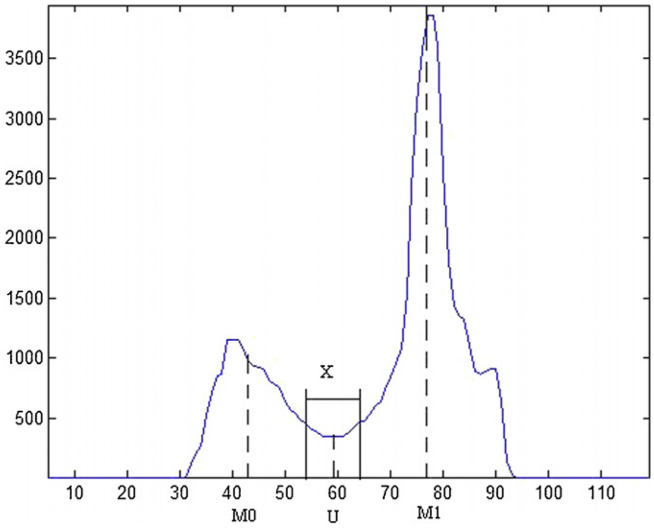

Figure 5. Peak detection method: the area in the threshold boundary measures the quality.

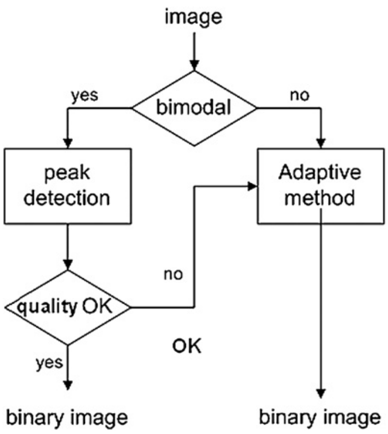

Figure 6. Binarization process.

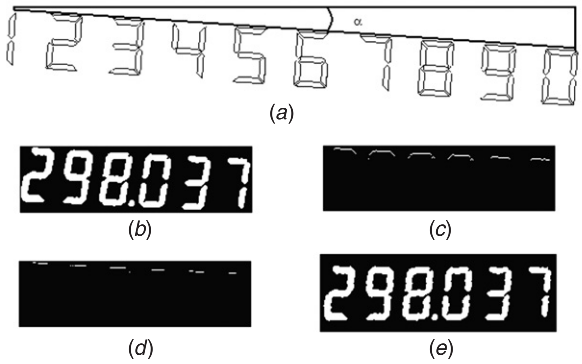

Figure 7. Angle correction: (*a*) method overview; (*b*) skewed image example; (*c*) extracted contour (vertical transition points); (*d*) cleaned contour after erasing points far from the mean and isolated ones; (*e*) corrected image.

advantage of big values on horizontal and vertical image projections to detect the edges.

A commonly used technique for character segmentation in a preprocessed row is based on horizontal projections [11]. Keeping in mind that we have to deal with instruments used in industrial environments, we apply an enhanced projection technique which is found to be more effective in noisy images. The aim of the method is to compute the position i in the projection vector as the dot product between the $(i-1)$st and $(i+1)$st column. The benefits of this technique in segmentation are shown in figure 8, obtaining deeper projection minima.

The segmentation process is complemented with a verification technique that checks, e.g., the aspect ratio or number of peaks and valleys of segmented character projections to detect linked characters (figure 9).

A redundant search of the decimal point is also applied to deal with problems like skewed characters that confuse the original projection. In the case of not finding the point in the first run, we start a search using a projection of only the lower part of the characters being already segmented (figure 10).

For digit recognition, we take advantage of two different classifiers. The first one is a standard structured classifier based on feature extraction and distance calculation. The selected features are character projections and directional components based on Kirsch Gradients [12]. For the classifier, a 1-nearest-neighbor algorithm is used. We have also tried various other classifiers (such as probabilistic neural networks, Gaussian classifiers and k-NN) but the best results were achieved for the 1-NN. The reason seems to be our multi-font situation, where the intra-class variance is greater than the inter-class variance for many cases.

As patterns for the 1-NN classifier we have chosen perfect ones (obtained from different computer font types such as Arial, Times, Digital, etc). We tried to use patterns from segmented input digits, but the 1-NN got better results for the artificial, perfect ones.

The second classifier is an original design based on human feature perception [13]. The objective is to inspect geometric features such as the presence of holes, lines or openings in variable positions around seven non-fixed outstanding regions in the character geometry (figure 11). These regions are compared to the known expectations for every character from 0 to 9. We obtain a ten-component binary vector (0–9) which has the value 0 (zero) or 1 (one) for each class, depending on its compatibility with the observed characteristics.

The aim of this method is not to serve as a global classifier able to work by itself, rather than to cooperate with another kind of classifier. The key is to differentiate the cases which are problematic for the first classifier. For this purpose, the feature perception method and the 1-NN classifier are combined in the way shown in figure 12. However, a similar fusion scheme can be used with any other kind of classifier.

The summary of the classification procedure is as follows.

- On the one hand, feature extraction and norm-1 distance to every pattern are computed to obtain a distance vector.
- On the other hand, the feature perception method, which results in a recognized character (or several possible characters), gives us a binary vector where its positions correspond to matching classes coded as ones and others coded as zeros.
- Distances corresponding to the classes recognized by the feature perception method are reduced by 20% (empirically) in the distance vector.
- Finally, the 1-NN is applied.

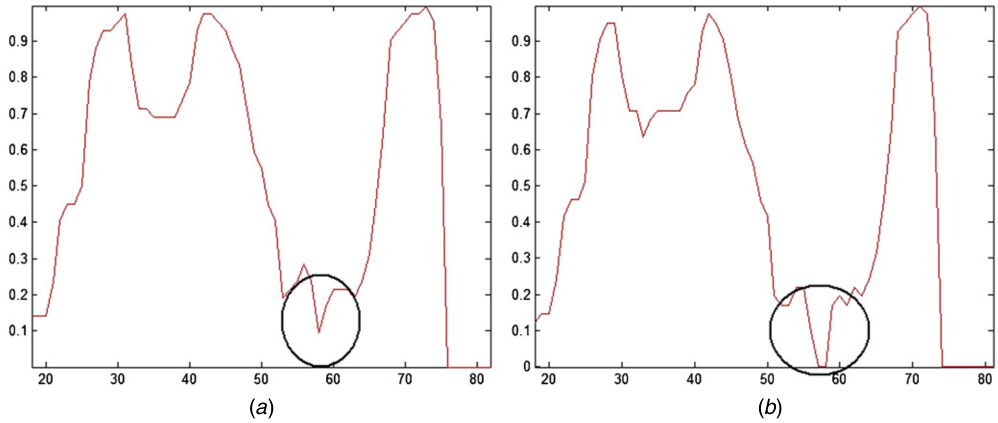

Figure 8. Comparison of (*a*) standard projection and (*b*) enhanced projection.

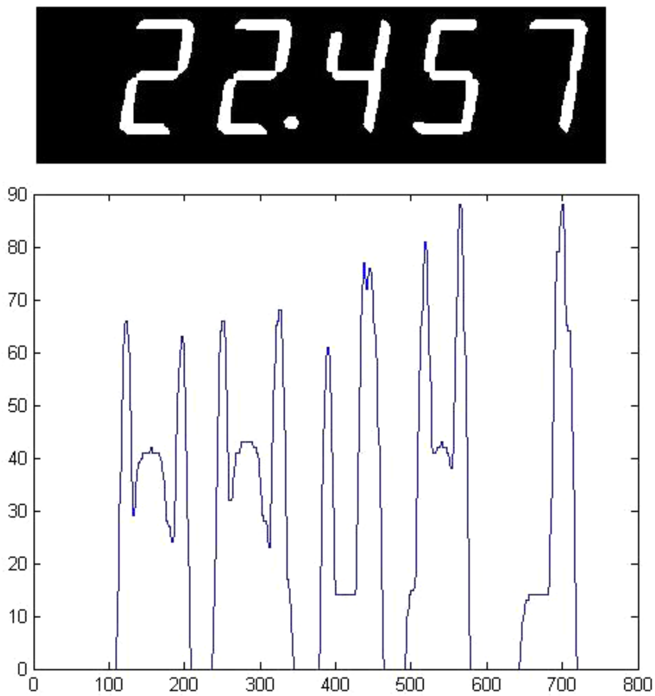

Figure 9. Row projection: a correctly segmented character has a maximum of two local valleys.

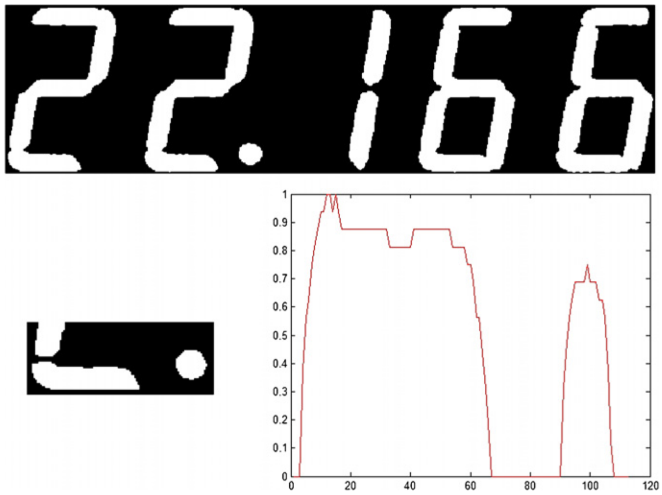

Figure 10. Above: skewed characters that make the point detection difficult. Below left: lower part of '2'. Below right: projection of fragment.

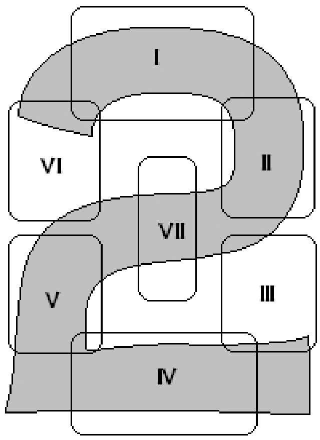

Figure 11. Areas of interest.

4. Results and discussion

To test the behavior of the system under real operation conditions, we have used 448 images obtained from 16 sequences of different instruments (figure 13). Note that we only take one sequence for every display. The system obtained the correct values 445 times, i.e. 99.33% recognition rate (measured on display images, not on individual digits). These results are achieved using the C-Cam BCi4 1280 × 1024 camera.

A test using a standard 640 × 480 pixel webcam (Labtec Webcam 1200, www.labtec.com) was also made. The achieved correct recognition rate is slightly lower (table 1 and figure 14) in our test setup. In a real operation scenario, however, a better recognition rate can be expected due to the fact that various images can be shot in the stable region of the measurements which is the case in a typical calibration process where the measurements are made under controlled conditions and when the instruments have achieved a stability point. At this time, several redundant measurements can be made, providing enough information to discard possible incorrect interpretations.

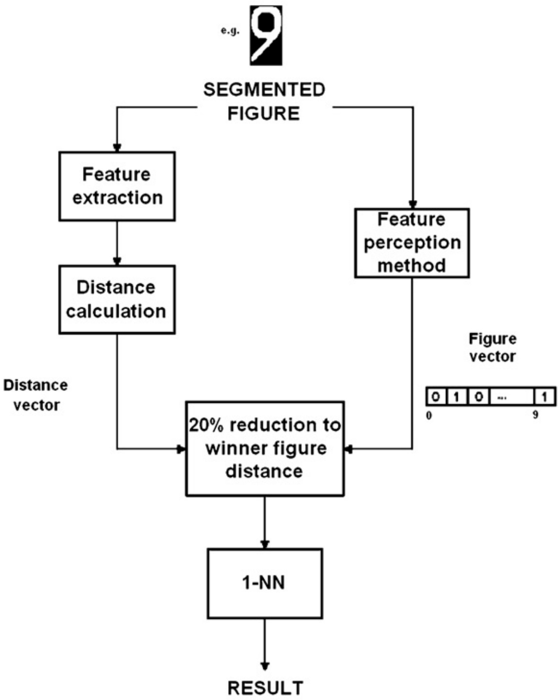

Figure 12. Classifier fusion.

Figure 13. Different fonts of the displays: (*a*) seven-segment skewed/not skewed, (*b*) effects of bubbles and scratched displays, (*c*) and graphic displays.

Table 1. Camera performance.

	Total	Correct	Incorrect	Correct (%)
C-Cam BCi4	448	445	3	99.33
Webcam	194	185	9	95.36

Errors are produced mainly in instruments with damaged displays (e.g. exhibiting scratches). Another cause of error is the capture of unstable displays where the digits are changing from one value to another (figure 15).

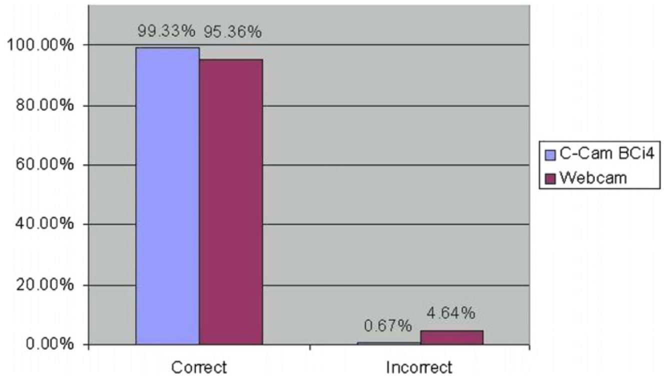

Figure 14. Camera performance comparison.

Figure 15. Problematic displays: (*a*) special display; note F above the decimals and (*b*) display in transition.

Table 2. System usability.

	Meters	(%)
Readable instruments	428	86.99
Incompatible format	10	2.03
Auto shutdown	31	6.30
Difficult displays	23	4.67
Total	492	100

As explained before, the objective of our system is to be able to read any kind of display without previous knowledge about its font type. In practice, there appear additional problems like unexpected types of displays, not disabled automatic shutdown function, etc. Under such conditions, there will always be a certain percentage of instruments that cannot be read by the system.

The impossibility of automatic reading is noticed by the laboratory technician in the initial phase of the calibration, so it will not produce errors in interpretation. Problematic instruments can be scheduled to be calibrated under manual supervision while the other ones can be handled automatically. It is important to take this fact into account since it is one key in the robustness of the system.

We have checked the instruments scheduled for calibration in the Temperature Department over a period of 4 weeks. We have contrasted the results of these tests with the historic data of thermometers and hygrometers of the years 2007 and 2008. Using this information, we have an estimation of the instruments that allow or do not allow automatic reading by the machine vision system. The instruments which do not allow automation are approximately 13% of the total (table 2 and figure 16). Note that auto shutdown is a problem beyond our system and should not be considered as an error.

Once tested for the thermometer calibration application, the system seems versatile enough to be adapted to read any kind of instruments exhibiting a numerical display.

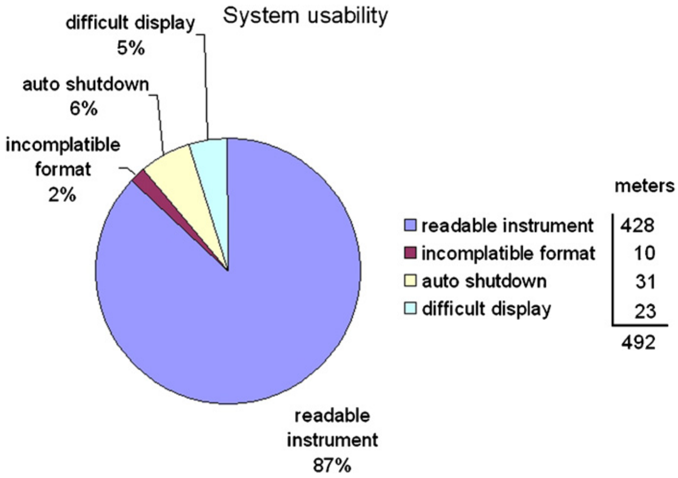

Figure 16. Estimation of the system usability.

Consequently, other potential applications, like the reading of Doppler speed meters in a running car for calibration purposes, are being implemented at this time.

There are also some future lines we are working on to improve the system.

- We could use sequences of images to solve the problem of displays in transition.
- We are also studying the effects (in global recognition rate) of adding new fonts to treat incompatible formats.
- The use of different preprocessing techniques, such as mathematical morphology or colorimetry, could be helpful to deal with difficult displays (e.g. damaged digits).
- We are working on enhancing the detection of the decimal point in the case of different locations (centered, upper position, etc) or different symbols (point, dash, etc).

5. Conclusions

We have designed and implemented a working system which is able to read almost any display of digital instrumentation. There are many potential applications where this system can be a helpful tool and provide benefits such as saving time and effort and avoiding human errors. The system has shifted the working plans of the technicians toward less routine work and more qualified activities. It allows automatic 24 h processes to be scheduled.

Related to the image processing and pattern recognition work, the analysis of human behavior can be very helpful in improving processes where machine vision is applied. The combination of a standard structured classifier and a new recognizer based on human feature perception achieves a much stronger system, which is capable of working with a large intra-class variance due to the presence of multiple fonts.

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References

[1] Gurevitch D 2004 Economic justification of laboratory automation *J. Assoc. Lab. Autom.* **9** 33–43
[2] Lee Y J, Chang K H, Chon J C and Oh C Y 2004 Automatic alignment method for calibration of hydrometers *Metrologia* **41** 100–4
[3] Hemming B and Lehto H 2002 Calibration of dial indicators using machine vision *Meas. Sci. Technol.* **13** 45–9
[4] Hemming B, Fagerholm A and Lassila A 2007 High-accuracy automatic machine vision based calibration of micrometers *Meas. Sci. Technol.* **18** 1655–60
[5] Mori S, Suen C Y and Yamamoto K 1992 Historical review of OCR research and development *Proc. IEEE* **80** 1029–58
[6] Correa Alegria F and Cruz Serra A 2000 Automatic calibration of analog and digital measuring instruments using computer vision *IEEE Trans. Instrum. Meas.* **49** 94–9
[7] Martín F 2003 Analysis tools for gray level histograms *Proc. Int. Conf. on Signal Processing, Pattern Recognition and Applications* ed M H Hamza (Rhodes, Greece: IASTED)
[8] Ohya J, Shio A and Akamatsu S 1994 Recognizing characters in scene images *IEEE Trans. Pattern Anal. Mach. Intell.* **16** 214–20
[9] Otsu N 1979 A threshold selection method for gray level histograms *IEEE Trans. Syst. Man Cybern.* **9** 62–6
[10] Gonzalez R C and Woods R E 2008 *Digital Image Processing* (Boston, MA: Prentice-Hall)
[11] Lu Y 1995 Machine printed character segmentation-an overview *Pattern Recognit.* **28** 67–80
[12] Kirsch R A 1971 Computer determination of the constituent structure of biological images *Comput. Biomed. Res.* **4** 315–28
[13] Vázquez-Fernández E, González-Jorge H, Dacal-Nieto A, Martín F and Formella A 2008 Human feature perception as a complementary method for digit recognition *Proc. Int. Conf. on Visualization, Imaging, and Image Processing* ed J J Villanueva (Palma de Mallorca, Spain: IASTED) pp 251–6