Automatic Power Consumption Reading on Digital Meters based on Adaptive Thresholds and Multiresolution Templates

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Abstract. *The reading of electricity consumption in Brazil is usually performed manually. One way to improve the time spent in the reading process is to provide a tool that recognizes the consumption based on images. In this context, this paper presents a method based on adaptive template matching for recognizing the power consumption displayed in digital power meters trough images. This is a part of SILEM - Mobile Reading System module, a validation system to automatically read and process images that are captured in the field, detect inconsistencies and at the same time perform automatic consumption recognition. The methodology results are promising, it recognized 72.18% of all meter consumption correctly, with 86.38% of all meter having at least 5 of 6 digits correctly recognized, minimizing human interactions to correct the read power consumption.*

1. Introduction

An electric meter is a device or equipment capable of measuring the electrical power consumption of a household, company, or electrical equipment. The electricity distribution companies carry out a monthly reading of the characters that represent the consumption of consumer units in kilowatts-hour (kWh). Most of the time, the reading process is performed manually by readers, which can result in reading errors and generate inconsistencies.

The companies CEMAR and CELPA located at Brazilian north/northeast use a mobile device and a portable printer to respectively collect the consumption and print the invoice of the customers. Readers typically record in the mobile device application the consumption displayed on the electricity meter. If there is no inconsistency, the invoice is generated, printed and delivered to the customer. However, in some cases, the reported consumption is outside the consumer's average consumption or the reader can not read it. In these cases, the application requests the image acquisition of the electricity meter and captures the geographical location of the reader as the record of the informed reading. The procedure may contain faults, such as image acquired without a meter, or presence of an image meter other than the corresponding one, etc.

In these companies, there is a revision group of workers that use the acquired image as one of the ways to analyze the inconsistency in reading. This is done in order to avoid errors in the consumption charged, thefts or frauds. That is, this group seeks to avoid non-technical losses. In Brazil, these losses represent a total of 44% of the total annual loss, which is of the order of 52 Terawatts/hour (TWh) [Vidinich and Nery 2009]. Every day, an average volume of 30,000 images is captured and sent for analysis before generating an invoice to the customer. Due to a large number of images to be evaluated, the audit is done by sampling.

However, it has been found that, in addition to the critical sector, it requires agile processing of the images, it is also necessary that the number of errors in the reading is minimized and streamlined. In order to reduce time spent reading the consumption, and also to make the process more precise, this paper presents a methodology for reading recognition in digital meters. Some works have proposed the automatic reading of the consumption of units based on images. In general, these works carry out image acquisition by fixing a camera positioned in front of the meter, focusing on the region of the digits of the equipment and then using image processing techniques and machine learning to perform the digits of the reading region [Parthiban and Palanisamy 2013, Zhang et al. 2016]. Another approach to automatic consumption reading is proposed based on the use of smart meters. Smart meters are devices that read and send them automatically via data network (SMS, GSM, PLC or wireless) [Popa 2011, Ali et al. 2012, Prapasawad et al. 2012].

Smart meters are, for the moment, a distant reality for power companies since the large number of installed assets and their exchange entails financial values that are impracticable at the moment. In this context, this paper describes an automated method to perform the recognition of reading in digital meters (LCD display), within the reality and peculiarities of CEMAR and CELPA companies. The method described here is part of SILEM - Mobile Reading System module, a validation system to automatically read and process images that are captured in the field, detect inconsistencies and perform automatic consumption recognition.

The remainder of this paper is organized as three more sections. Section 2 presents the proposed methodology. The results are presented and discussed in Section 3 and finally the final remarks are discussed in section 4.

2. Proposed Methodology

The images acquired through SILEM by CEMAR and CELPA have several aspects that difficult its recognition. These aspects are mainly related to lighting factors (shadow, LCD display wear), image acquisition quality (distance from the meter, irregular positioning with inclinations on all axes, blurring), and noise (generated by weather conditions, waste on liquid crystal display (LCD) protective polyurethane box, consumer interference's). These aspects make a methodology for the recognition of digits in a global way impossible. It is necessary to use adaptive techniques that perceive the specific environment to react properly, generating the best response.

Thus, the proposed methodology makes use of several techniques, but combined produce highly adaptive and robust solutions. We combine a Multiresolution Template Matching [Brunelli 2009] to locate the digit within a window. This window is preprocessed by three adaptive thresholding methods: Sauvola's [Sauvola et al. 1997], Wolf's [Wolf and Jolion 2004] and Mean Dependent Local Histogram [Rafael Gonzalez and Woods 2002] in order to improve noise robustness.

2.1. Background

Template Matching is a high-level computer vision technique that identifies parts in an image that matches a predefined template. The matching process is coded by calculating the similarity of the template with sliding windows of the same dimensions within the image. One way to calculate matching is through Equation 1 that measures the square difference between the template T and a window in image I.

$$dist(x,y) = \sum_{x',y'} (T(x',y') - I(x+x', y+y'))^2 \quad (1)$$

where x' and y' are the coordinates in the T template of image I.

Three adaptive thresholding techniques are combined in this methodology to make it more robust to imperfections in images and also to noise. The algorithm proposed by Sauvola [Sauvola et al. 1997] calculates the best cut based on the standard deviation of the grayscale variation (S) in the image:

$$T_{Sauvola} = m * (1 - k * (1 - \frac{S}{R})) \quad (2)$$

where m is the mean value of the pixels, k and R are constants of 0.5 and 128. This algorithm is suitable when there is a significant distance between the pixel values of the digit in relation to the background.

The algorithm proposed by Wolf [Wolf and Jolion 2004] normalizes the image contrast and the average value of the gray tones by calculating the best threshold using:

$$T_{Wolf} = (1 - k) * m + k * Max + k * \frac{S}{Min}(m - Max) \quad (3)$$

where k is a constant set to 0.5, Min is the smallest gray tone value present in the image and Max is the largest gray tone, and S is the highest standard deviation of all analyzed windows. The method has the same principle as the Sauvola method but seeks to be more robust to local noises.

The Mean Dependent Local Histogram calculates the best threshold value for each pixel, taking into account the average neighborhood values and a cut-off factor C equal to 128. Based on Equation 4, if the image I at point (x,y) is less than T, then its value will be eliminated.

$$T(x,y) = \frac{\sum_{x',y'} I(x',y')}{n} - C \quad (4)$$

where x' and y' are pixels coordinates inside the surrounding window of the pixel.

2.2. Methodology Steps

The combination of the techniques described above forms the proposed methodology. The three steps of the methodology are presented in Figure 1.

Explaining the methodology, the first step is to create digit templates that can be used for recognition. Because there are several types of meters with different source patterns, templates have been created for each specific model (Figure 2) capturing different fonts and orientations. Since we have *a priori* information of the meter type, it is possible to choose the appropriate template for each display by the maximum similarity with the template. Each of the seven segments (named from A to G) of each template is codified with a different color starting with the value 32 (for segment A), increasing by 32, reaching 224. The color scheme turn simple to identify matching and identify it with the proper segment.

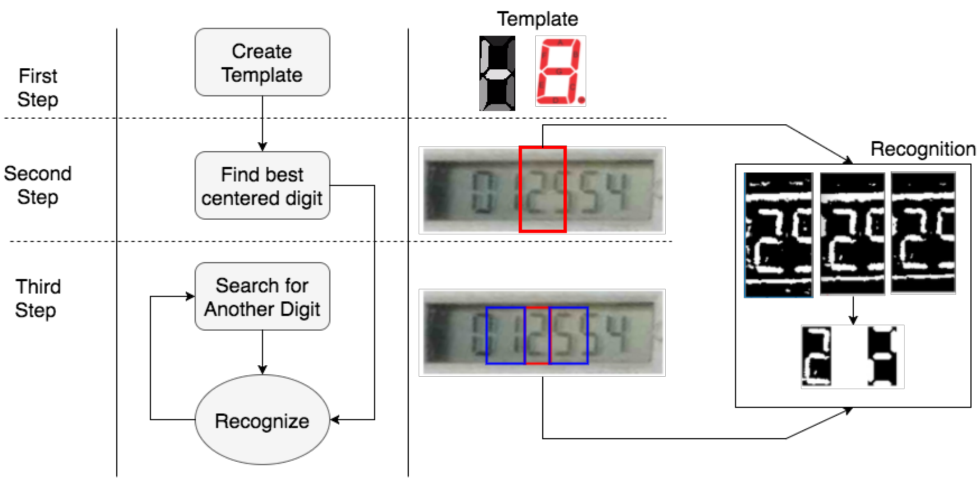


Figure 1. Steps of proposed methodology

With the templates, the second step is to find the most center digit in the display. From this digit, we estimate the height and width of the digits in the display. To perform this step initially is necessary to determine the central pixel of the display based on the dimensions of the image. Thus, with the central pixel, it is generated a bounding box with a width tow times greater than the template and with a height equal to the display. This is done because at first, we do not know the size of the digit. We adapt the size of the template starting from 60% of it's original size to 200% while the first digit is not localized. When it is localized, the same size is used for the others digits.

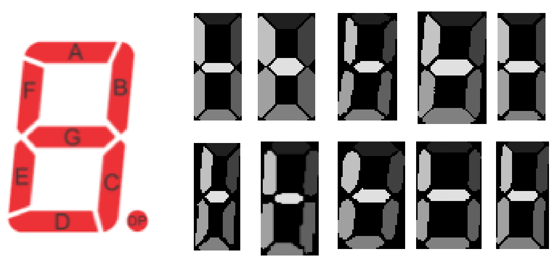


Figure 2. Used variations of templates for digit detection

The final step is the application of the adaptive threshold (Section 2.1) and comparison with each digit template. With this process, we look for the digit. The recognition of the digit is based on the following indexes:

- Matching Index (M): measure how similar the window tested is with the template;
- Complementary Matching Index (IM): measures how similar the window tested is with the complementary template;
- Noise Index (N): measures how similar the window tested is with areas that are not part of the digit inside the template;
- Loss Index (L): matching error index.

The indices are combined through the relationship proposed in Equation 5. The objective is to inform the degree of similarity between the template and the region tested for digit recognition, considering losses, noise, and other factors. The recognized digit is the one that gets the highest similarity value.

$$S = M * (1 - IM) * (1 - N) * (1 - L) \tag{5}$$

Equation 5 allows us to consider the matching with a number of losses generated by the noise, matching error and error with the complementary matching. Once the matching has been high but has had many losses, it is weighted in order to have the best possible similarity in the three adaptive thresholds available. We use a Boosting ensemble algorithm with linear cuts [Dietterich et al. 2000] in order to select the best weight of each index to improve the precision.

A fundamental characteristic present in Equation 5 is that regions with higher noise presence will have a lower index of similarity and therefore chance to be chosen in the recognition.

The third step consists of searching in both directions for new digits, whereas the new digits never overlap the center digit located in the second step. It is assumed that the new digits have the same width and length as the center digit. The process of searching and matching is exactly the same as described in the second step. The stop point of the process is when there are no more digits to be detected.

3. Results

To validate the work, we used an image database of meters extracted from the databases of electrical companies CEMAR/CELPA. The images were acquired using portable cellphones with Android operating system, and cameras with resolution ranging from 5 to 8 megapixels.

It was acquired 2128 images of LCD displays from digital meters. Each display was captured manually by positioning the SILEM application on the meter. All meter displays has 6 digits. Each display is associated with the consumption value and the meter model, both of which are entered manually. It should be noted that the display digits may not be visible due to shading problems or loss of acquisition.

For the company, the only consistent result is the correct recognition of all digits. The result is evaluated in terms of the number of digits recognized within the display: all digits recognized (All), 5 or more (5+), 4 or more (4+) and 3 or more (3+). The main objective of the methodology is to recognize all digits of the display, which also gives the measurement of the consumption. In these cases, the reader with SILEM does not need to correct any information. However, partial hits are also valued to minimize the reader's effort to correct the consumption manually. We present in Table 1 the results obtained by the methodology.

Analyzing the results, we found that 72.18% of the displays were fully recognized. This result is justified because of the variability of the images, as well as the quality of the input images (Figure 3 (c-d)).

Table 1. Results of the proposed adaptive methodology for digit recognition

Digits	Displays	Precision (%)
All	1536	72.18
5+	1838	86.38
4+	1945	91.40
3+	2017	94.78

From all images, we verified that in 94.78% of the displays at least 3 digits were recognized, and in 91.40% at least 4 digits were recognized, and in 86.38% at least 5 digits were correctly recognized. The result shows that in the majority of the displays the methodology was able to perform a partial reading, causing the reader to report only a small fraction of the digits, making reading work more efficient and reliable. The effectiveness of the methodology is also demonstrated by having a general recognition accuracy per digit of 90.29%. This means that of the 12.768 digits of the 2128 displays, the methodology was able to correct recognize 11.529 digits.

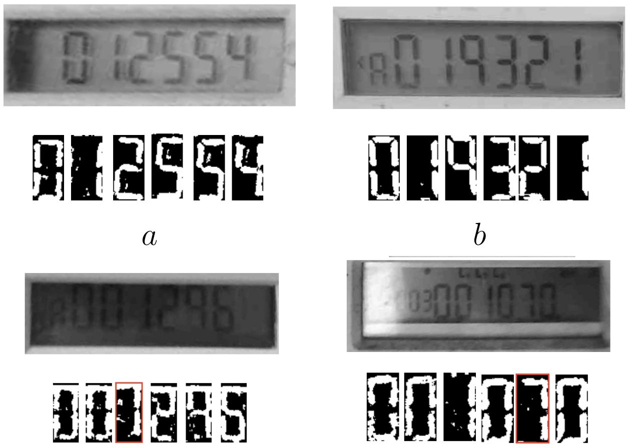
The literature presents other works of digit recognition, but so far, none has been found that uses as a base images of electrical meters, in uncontrolled environments or even in industrial application. This fact made it difficult to compare them with related labor.

Figure 3 presents some case studies of correctness and error. In cases of error, a single-digit error was generated. Figure 3 (c) shows an error in the threshold process that was not able to isolate digit 1 because of the inclination of the camera device at the time of acquisition. In the case of Figure 3 (d) the digit 7 is recognized as digit 1 because the template size used is larger than the size of the segmented digit.

4. Conclusions

This work presented a method based on the combination of template matching and adaptive thresholds, with the objective of recognizing the electric energy consumption per image obtained from digital meters with LCD display.

The great challenge was to create a robust method for variations in illumination, inclination, noise, waste on electric meter protectors and other imperfections during image capture. This methodology proved to be promising by achieving a total recognition of



a b

c d

Figure 3. Study cases: (a) and (b) demonstrates correct cases where all digits where recognized, respectively 012554 and 019321 (c) and (d) demonstrates cases where the methodology loss one digit, respectively 007295 and 001010

49.55% of displays (on a base of 1322 meter displays) with an individual digit accuracy of 82.59%. The results demonstrate that even under severe conditions, the methodology was able to give conclusive answers that improve the process of reading of electric consumption, making available to the electric company a low cost and efficient method for measurement.

Although the results were promising, it is necessary to use invariant rotation and digit detection scale techniques, since this was the greatest cause of errors in the methodology. We also intend to combine digit recognition techniques, such as Histogram of Oriented Gradients and Convolutional Neural Networks, in order to make the method more robust to outliers.

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