Scientific Cooperations International Workshops on Electrical and Computer Engineering Subfields
22-23 August 2014, Koc University, ISTANBUL/TURKEY

Vision based mobile Gas-Meter Reading

Machine Learning method and application on real cases

Mehdi Chouiten
WASSA
5 Rue de l'Eglise, 92100, Boulogne-Billancourt,
Region of Paris, France
mehdi.chouiten@wassa.fr

Peter Schaeffer
WASSA
5 Rue de l'Eglise, 92100, Boulogne-Billancourt,
Region of Paris, France
peter.schaeffer@wassa.fr

Abstract— **The constant increase of smartphones computation capabilities has allowed a growing number of applications. This, combined with the improvements of sensors quality and to third generation (3G) and fourth generation (4G) telecommunication network coverage, made possible the development of robust and reliable computer vision applications exchanging significant amount of data.**

In the gas distribution industry, the consumption reporting is a very important issue. In France, the major gas provider (GDF Suez) plans to deploy 11 million smart meters within 2022. In the meantime, employees of GDF are periodically sent to manually collect data from customers.

In this paper, we present a solution developed for GDF – Suez to solve this problem using mobile technologies and computer vision algorithms.

Keywords; Mobile, Computer Vision, Segmentation, Gas-Meter, OCR, machine learning

I. INTRODUCTION

Smartphones are becoming the prefered plateform for developing innovative applications in several domains like computer vision or augmented reality.

First of all, they are now widely used, a recent study [1] show that more than half of U.S people has one. It's obvious that smartphones are now mainstream, and their use will continue to grow in the near future.

Secondly, they are becoming more and more powerfull, with improved computing and imaging capabilities, it's now possible to embedd in a mobile applications more computer intensive task that were even not possible a few years earlier on desktop computers. For example, the CPU is 40 times more efficient in the latest iPhone comparing to the initial one released in 2007.

Lastly, they are permently connected to fast and reliable cellular networks allowing cloud based mobile applications, for example for data storage or computing of tasks that are still to heavy to be performed on mobile devices.

The challenge we are going to tackle is to find an easy and affordable way to invoice gas customer by allowing the client to automatically read his gas meter through a smartphone application. This task is currently performed by employees sent to the client home to read the counter. Currently, this procedure is very expensive for energy providers and they are searching new ways to lower the cost of this procedure.

Our Solution consist of an automated read and send of the gas-meter current value through a smartphone camera.

II. AIM AND MOTIVATION

Capitalizing on the growth of mobile usage and the inherent increase in performances related to computation capabilities and to network speed, the challenge we are going to tackle is to find an easy and affordable way to bill gas customers by allowing the customers to automatically read their gas-meter through a smartphone application. This task is currently performed by human operators sent to the client's home to read the gas-meter.

Currently, this procedure can be very costly for energy providers and they are searching new ways to lower the cost of this procedure. Among the solutions is to have smart meters connected to the network. Though this solution is effective, the governements and providers plans to replace the existing meters takes from 5 to 10 years depending on countries and the cost of this replacement is valued to bilions of dollars.

Our goal is to provide a solution that consists of an automated gas-meter reading application that works on most smartphones using only the embedded camera and that is able to record and send the data to the provider.

III. Previous work

Though it is not widespread, the challenge of being able to recognize consumption digits of meters (gas-meters, electricity meters…) is not new. Some previous works have been initiated, and some of them include the use of computer vision. Though most of these systems are not optimized for a mobile device, we will present thei main features and used approaches. We will then have a discussion on their accuracy and introduce the need of a new approach.

In 2011, Cai and al. [2] has initiated research on electric meter recognition using computer vision. The electric meter is considered as a Region Of Interest (ROI) characterized by its color. This detection is then followed by a post processing step aiming to achieve a finer detection taking in consideration the format of the display of the consumption digits.

The character segmentation is done after threshold of the detected zone, some morphologic operations and character segmentation. The numbers classification is based on the number of white pixels.

The presented results are superior to 90% success. These results are based on very specific meters and limited database.

One of the most recent works on the subject is the research done by Vanetti and al. [3]. Using a set of supervised neural models able to detect an object in a cognitive manner. Each node us trained on a set of different points extracted from the training database. This is used for both the counter detection and for digit segmentation.

Within the counter detection step, the segmentation presented some lack of precision in the boundaries. This resulted in missing some parts of the image and sometimes having unnecessary background included in the region detected. To avoid this problem, the team used fast watersheds algorithm.

For the classification of the digits, an SVM with radial function based kernel is used as a discriminative model. The final accuracy of this system was from 45% to 90% depending on the number of noisy pixels.

In the same field, Grafmüller and Bayerer [4] have worked on the improvement of the performance of character recognition algorithms for industrial applications. They use prior knowledge to help the system to take advantage from this information and make a better decision.
The image captured is not binarized since all gray levels are kept. Also, the information of lines and skew is taken in consideration in all the process.
A study comparing different combinations is performed and the result is that the best system is the one using prior knowledge, using DCT (Discrete Cosine Transform) as a feature (instead of PCA) and having SVM as a classifier for individual characters.

The two first systems are quite close to our application. However, their generalization to a heterogeneous set of gas-meters seems complicated and their invariance to light and color variations are not robust because of the chosen features. The naïve OCR used in [2] counting the number of pixels is also a minus.
Finally, our need is to have a mobile application that performs on very heterogeneous devices (including low computation capabilities devices). That is why we introduce our new approach.

IV. Context and Constraints

The application has been designed to fulfill the previously stated objective. However, while studying the needs of the users, we identified some constraints to respect.

First, the application should be able to address most of the users. Today, the market of smartphones is dominated by Apple iPhones based on iOS and Android system based smartphones. Combined, these 2 OS cover more than 96% [5] of the smartphones market. This is why we decided to target the 2 platforms.

Second constraint is about the computation time. Though we want to maximize the performance, it doesn't make sense for the user to wait longer than typing the digits manually. That is why we defined a 3 seconds maximum computation time on any device. The algorithm adapts the processing depending on the device and can work in degraded mode. Also, some gas-meters being in cellars and places without network connection, it was necessary to perform the computation offline.

Finally, another constraint is to allow users to see their history and allow GDF to make statistics of the usage of the application and eventual effects on the user consumption.

V. Solution

To answer the need respecting the previously stated constraints. We proposed a solution packaged as an SDK embeddable on android as well as iOS platforms. The SDK is coded in C++ but also provides all necessary wrappers to be easily included in an java or objective-c application. The solution includes a history of all reports and captured images. It also involves a back-office destined to GDF.

Algorithmically speaking, the solution follows the steps described in figure 1.

First of all, the user has to log into the application with his credentials. Then he simply chooses to add a new report. The camera is then launched. A visual assistant helps the user to target the right zone (the region containing the digits). After having some frames captured, the capture stops and the processing is performed. The solution could process at the same time it makes the capture but keeping in mind that we want the solution to run on most smartphones including old ones, we noticed that some low computation capabilities phones couldn't handle both and multithreading was not really useful for such phones.

The next step is then to detect the ROI (Region Of Interest). It is done using a Haar cascade (Viola and Jones method). The obtained ROI is then converted to HSV (Hue, Saturation, Value) format. We then normalize the obtained cropped image on V channel. After that, we divide the zone in 2 sub-images.One includes the useful consumption part (black part that represents the consumption in cubic meters) and the other is the decimal part in red.

On each of these 2 images, a thresholding is done using Otsu method [6]. Some morphological operations are performed on these two images before blob detection. The transformations include erosion/dilation depending on the result of thresholding. The obtained blobs are then filtered. Too small blobs are deleted. Blobs that don't respect aspect ratios of digits are also eliminated. As shown in figure 2, the obtained blobs represent the digits. These blobs are then aligned. Depending on the result of the alignment, some morphologic operations are performed (to avoid blobs fusion for example). Our blobs are then ready to be passed to the OCR (Optical Character Recognition).

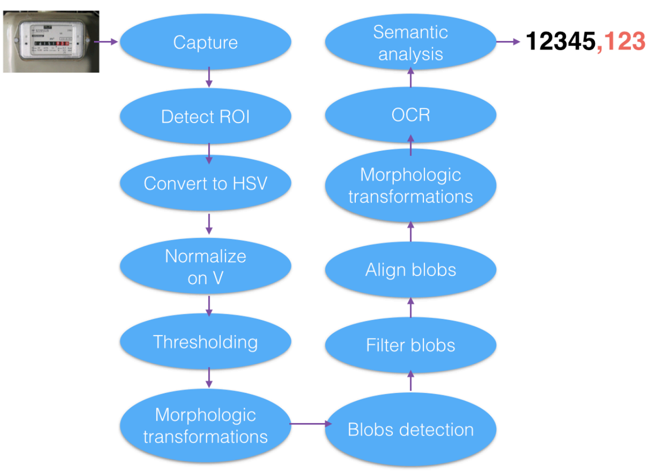

Figure 1. Main steps of the solution

We used GOCR open source OCR in our project because it's very lightweight and because the result of our pre-processing are good enough to produce easy to recognize image. The last step is a semantic analysis verifying the coherence of the consumption depending on history and consumption estimations. If the consumption is valid (eg. not inferior to previous one or too large comparing to estimates…) then the report is stored and sent to GDF back-office.

Figure 2. An example of the output of the algorithm after the "filter blob" step (top: original image, bottom: result).

If the user is not satisfied with the detection. He still can modify the wrong characters. The algorithm takes in consideration this modification and includes it in a learning database for results improvement.

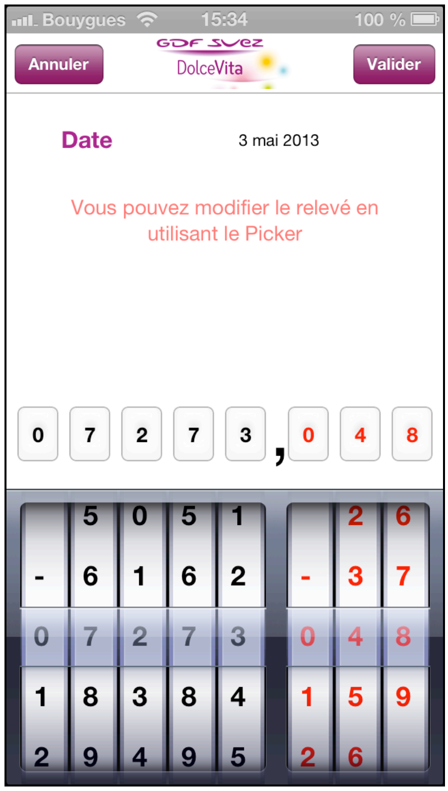

Figure 3. Result interface (allowing the user to change before submit)

VI. Tests

Tests of the solution have been performed. We performed tests on 20 devices (16 android-based and 4 iOS-based phones). The tests have been performed on heterogeneous gas-meters representing the variety of GDF customers' gas-meters. Tests have been made on 5 different models of gas-meters.

The obtained results are listed below (Table 1). Performance on android phones is lower due to the heterogeneous phones including some low-budget phones having lower computation capabilities and lower resolution camera sensors.
The test phase is divided in 2 different situations. We tested the vision algorithm alone and the full solution including the semantic analysis (comparing to previous consumptions and future consumption estimates).

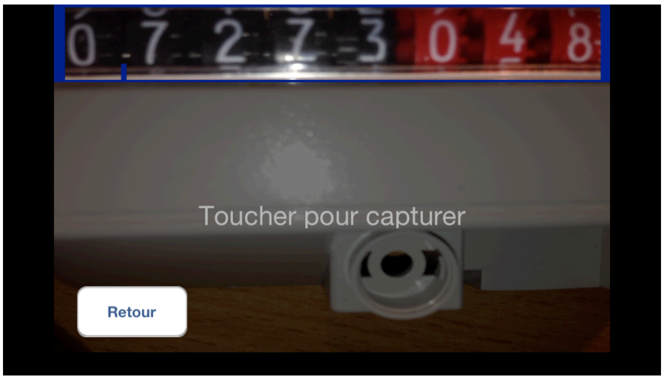

Figure 4. The capture interface

	Pure Vision	Vision + Semantic
Android phones	87 %	92%
iOS phones	92 %	> 99%
Average	89%	93 %

Table 1. Test results (success rate).

The tests include particular situations like very dark places, light reflections, unreadable characters, unclear choices (see Figure 5). The success rates given on Table1 are based on individual digits and not full consumption. This means that if we have on one test 7 digits correct on a total of 8. We will consider 87.5% correct on this test and not consider the whole test as wrong.

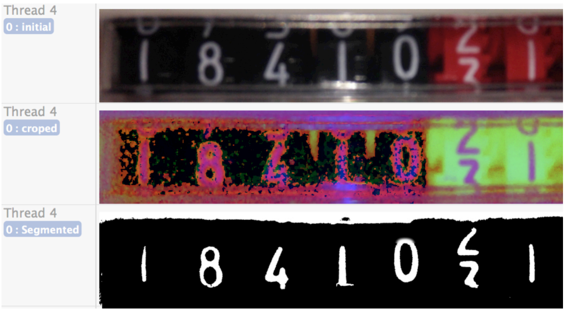

Figure 5. Case of unreadable character (impossible to decide 2 or 3 on 7th character)

VII. Conclusion and Future Work

In this paper, we proposed an innovative solution that avoids a huge amount of money spending and time wasting to send human operators to collect information directly from the customers. Our solution answers the needs and constraints specified in the paper working in a reasonable time on the 2 main mobile Operation Systems and supporting low computation capabilities and offline processing. The machine learning techniques involved and the algorithm itself proved to be quite efficient especially when combined with prior information (semantic analysis).

It is possible to improve the results by having a larger set of training and we can also make a more adaptable algorithm that maximizes performance depending on the device power. We can also have a better management of situations were we can't decide. We currently simply select one of the available choices and in case we don't have any, we select the same digit as what we have in history.

VIII. Aknowledgements

We express our gratitude to GDF-Suez for contributing to this research effort. First, financially. And also for making so many gas-meters models images available and for involving some of their users for the test phase.

IX. References

[1] Aaron Smith. Smartphone ownership 2013. Technical report, pewinternet, 2013.

[2] Zemin Cai, Chuliang Wei, Ye Yuan, An Efficient Method for Electric Meter Readings Automatic Location and Recognition, Procedia Engineering, Volume 23, 2011, Pages 565-571, ISSN 1877-7058.

[3] Marco Vanetti, Ignazio Gallo, and Angelo Nodari. 2013. GAS meter reading from real world images using a multi-net system. *Pattern Recogn. Lett.* 34, 5 (April 2013), 519-526.

[4] Martin Grafmüller, Jürgen Beyerer, Performance improvement of character recognition in industrial applications using prior knowledge for more reliable segmentation, Expert Systems with Applications, Volume 40, Issue 17, 1 December 2013, Pages 6955-6963, ISSN 0957-4174.

[5] IDC, Smartphone OS Market Share, Q1 2014

[6] Nobuyuki Otsu, « A threshold selection method from gray-level histograms », *IEEE Trans. Sys., Man., Cyber.*, vol. 9, 1979, p. 62–66