DEVELOPMENT AND IMPLEMENTATION OF SOFTWARE SOLUTIONS FOR WEEE IDENTIFICATION, WEIGHING AND SORTING

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ABSTRACT:
INCREASING THE LEVEL OF WASTE ELECTRICAL AND ELECTRONIC EQUIPMENT (WEEE) SEPARATE COLLECTION REPRESENTS A PRIORITY IN THE CONTEXT OF HIGH REQUIREMENTS FOR MATERIAL RESOURCES. NOWADAYS, WEEE COLLECTING SYSTEMS ARE NOT FULLY AUTOMATED, HUMAN OPERATORS ARE STILL USED FOR WEEE IDENTIFICATION, WEIGHING, SORTING, TRANSPORTING AND STORING. IN ORDER TO OBTAIN A FULL AUTOMATED WEEE COLLECTING SYSTEM, THE WASTE IDENTIFICATION PART IS THE HARDEST TO ACHIEVE. IN THIS PAPER, SOME PRELIMINARY RESEARCH RESULTS REGARDING A SOFTWARE DEVELOPMENT AND IMPLEMENTATION FOR THE WEEE IDENTIFICATION, WEIGHING AND SORTING ARE PRESENTED. THE MAIN COMPONENTS OF THE WEEE IDENTIFICATION SYSTEM ARE DESCRIBED, SUCH AS: A VISION SYSTEM, A METAL COMPONENTS DETECTION SYSTEM, AN INTEGRATED ELECTRONIC WEIGHING SCALE, A POS PRINTER AND A READING INTERFACE.

KEY WORDS: SOFTWARE DEVELOPMENT, WEEE, IDENTIFICATION, VISION SYSTEM

INTRODUCTION

Technological innovation accelerates the replacement of equipment which generates an increase of waste electrical and electronic equipment (WEEE)[6]. More and more WEEEs need to be collected for recycling, that is why, an improvement of the WEEE separate collecting systems is needed in terms of automation. Currently, human operators are still used for

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[6] Xueyi Guo, Yongzhu Zhang and Kaihua Xu; Metallurgical recovery of metals from Waste Electrical and Electronic Equipment (WEEE) in PRC, Metal Sustenability – Global Challenges, Consequnces and Prospects, John Wiley&Sons, 2016

WEEE identification, weighing and sorting. In order to increase the level of WEEEs collection it is necessary to obtain a full automated WEEE collecting system.

For some categories of WEEE, product and producer identifiers started to be used in the last decade. In this way, an automated identification of using the RFID technology became possible[7]. Plosek and Fiser propose an automated recognition system able to identify the position of general labels and manufacturers' logos, to determine the producer and to relate unstructured information from labels with a specific model of electrical equipment[8]. But the identification problem still remains because the majority of electronic and electric equipment do not contain such identifiers and labels or logos are missing because of product utilization or handling. On WEEE separate collection for recycling a complete automated identification system is needed. This system should include a vision system for an accurate waste identification. The identification is based on machine vision, a convolutive neural network specifically trained to recognize electrical and electronic equipment.

The proposed system consists of:

- a vision system (video camera, neural network application);
- a metal component detection system and a read interface;
- a control system for the conveyor;
- an integrated electronic weighing scale on the conveyor and a reading interface;
- a POS printer and a print interface.

In the following sections, some preliminary research results regarding a software development and implementation for the WEEE identification, weighing and sorting will be presented.

THE VISION SYSTEM

For image analysis, we used Caffe. Caffe is a deep learning environment developed for expressiveness, speed and modularity. This development environment was launched by Berkeley AI Research (BAIR) and by the open source community of developers. Yangqing Jia created the project during his doctorate at UC Berkeley. Caffe is available under the BSD 2-Clause license.

Expressive architecture encourages application and innovation. Models and optimization are defined by configuration without coding.

Processing speed makes Caffe perfect for research experiments and industry implementation. Caffe can process over 60 million images per day with a single NVIDIA K40 * GPU. About 1ms / inferential image and 4 ms/ image for learning, the more recent versions of the library being even faster. Caffe is one of the fastest deployments available.

Caffe is implemented in various academic research projects, prototypes and even large-scale industrial applications in machine vision, voice recognition and multimedia.[9]

To create a Caffe model, the model architecture must be defined in a prototype definition file. For this application, we used the GoogleNet model. (figure 1)

Caffe layers and their parameters are defined in the protocol buffer definitions for the caffe.proto project.

To train the model we need to prepair all the training sets images and create the lmdb databases. The prepairing process consist in:

- Run histogram equalization on all training images. Histogram equalization is a technique for adjusting the contrast of images.
- Resize all training images to a 227x227 format.

[7] Christian Butz; Product Individual Sorting and Identification Systems to organize WEEE obligations, Advances in Life Cycle Engineering for Sustainable Manufacturing Businesses, Springer, 2007

[8] Lukas Plosek and Martin Fiser; Modern approaches to identification of collected WEEE, MendelNet, 2014

[9] Caffe Deep Learning Framework http://caffe.berkeleyvision.org/

- Divide the training data into 2 sets: One for training (5/6 of images) and the other for validation (1/6 of images). The training set is used to train the model, and the validation set is used to calculate the accuracy of the model.
- Store the training and validation in 2 LMDB databases. train_lmdb for training the model and validation_lmbd for model evaluation.
- generate the mean image of training data
- After defining the model and the solver, we can start training the model

After training the Caffe model, its files have been converted into binary blob so they can be read by CaffeJS through http.

The image captured by the video camera is analyzed and the analysis results are stored in a target-score array of 5 decreasing order estimates by precision score. Subsequently, this array is analyzed element-by-element and compared by score with the elements of a classification database (electronics, small home appliances and large home appliances). If at least one of the array elements is found in the database corresponding to one of the three categories mentioned above, the application validates the object's identification as being recyclable and determines the price by category and by the weight read by the scale. There are higher weight limitations, for a certain element identified, we have maximum permissible weight, so we can eliminate fraud attempts by overloading weighing objects by the user.

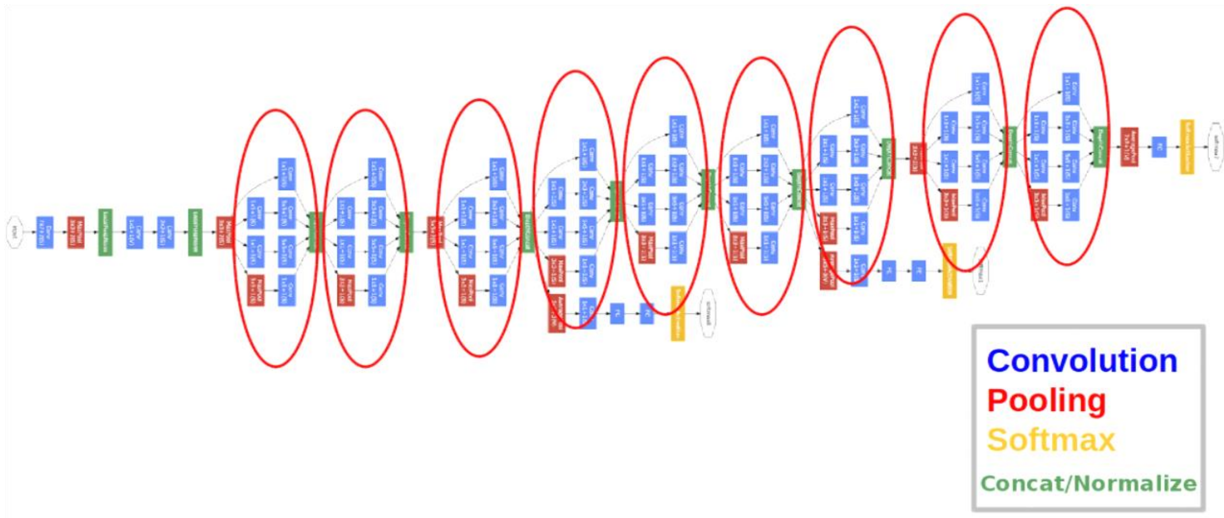

Figure 1. GoogleNet Chart - 9 Inception Modules, 22 Layers[10]

Subsequently, the type of the object, the category it belongs to, the proposed weight and redemption price are displayed. The user can accept or cancel the transaction. If the transaction is accepted, the item is taken over by the conveyor and stored and a receipt will be printed to the user.

The application has a web touch-screen interface that can run in kiosk mode directly into a browser on any OS (Windows, OSX, Linux, Android). Recorded transactions are transmitted to a central server (Figure 3).

THE METAL DETECTION SYSTEM AND THE READING INTERFACE

As a further safety measure, a metal detector that can read the metal content (ferrous or non-ferrous part) of the recycled object.

[10] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich; Going Deeper with Convolutions - (Submitted on 17 Sep 2014) https://arxiv.org/abs/ 1409.4842

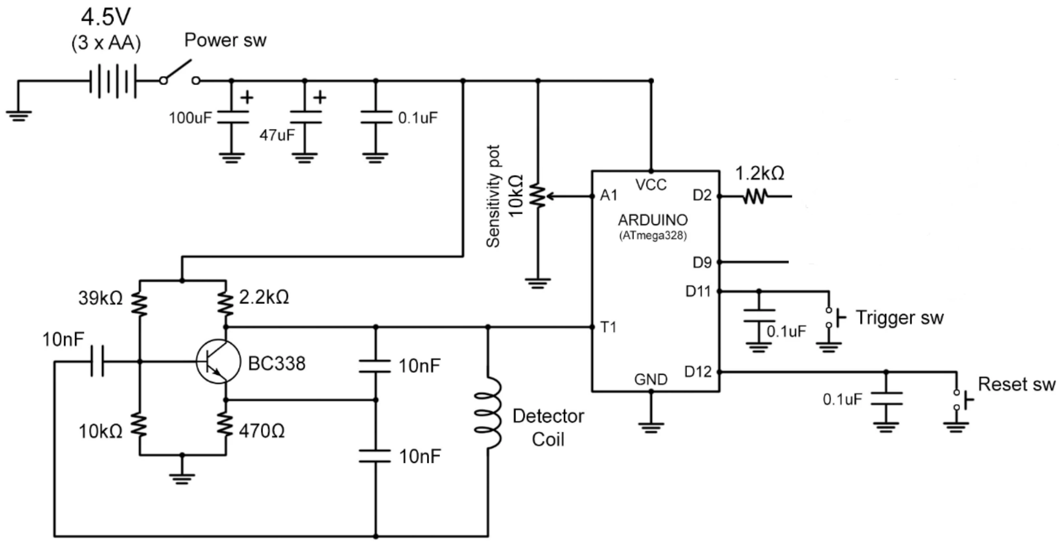

Figure 2. Scheme of the metal detector

The detector is made with an Arduino Uno development board[11] and a Colpitts oscillator connected to the T1 pin of the development board. Pin A1 is connected to the potentiometer cursor, which allows the sensitivity adjustment (see Figure 2). The digital outputs D2 and D9 provide the output signal proportional to the oscillator frequency variation due to the proximity of a metallic object.

Since the oscillation at the oscillating circuit nodes before and after the inductor is offset by 180°, one of the nodes will provide the oscillation at the base of the transistor, which will amplify and reverse the signal from the collector, then return it to the other oscillating circuit node. This whole circuit is called the Colpitts oscillator.

The Colpitts oscillator above provides a constant oscillation with a frequency in the 100kHz range. Metals in recycled articles changing the permeability of the inductor core, will fluctuate this frequency around 10 kHz. Arduino will store the fixed frequency and will continuously compare the input frequency of the detector circuit with the stored frequency.

THE CONTROL SYSTEM FOR THE CONVEYOR

To control the conveyor, we used an Arduino Uno development board and the JohnyFive[12] open source IoT library integrated with socket.io[13] and node.js.[14]

The development board operates two relays to command the conveyor direction of movement.

In the first step of the collecting process, the user places the product on the conveyor in the pickup area and clicks the Load button. By pressing this button, the Arduino command is sent via USB and commands the relay for the proper movement direction of the conveyor. The operation is timed for a predetermined period so that the object reaches the visual scanning area. After identifying the category, weight and the proposed price are displayed. The user can accept or cancel the transaction. By pressing one of the two buttons, Arduino is driven to command one of the two relays, and the object is stored or returned to the user.

[11] Arduino; https://www.arduino.cc/
[12] Johny Five JavaScript Robotics & IoT Platform http://johnny-five.io/
[13] Socket.io https://socket.io/
[14] Node.js https://nodejs.org/en/

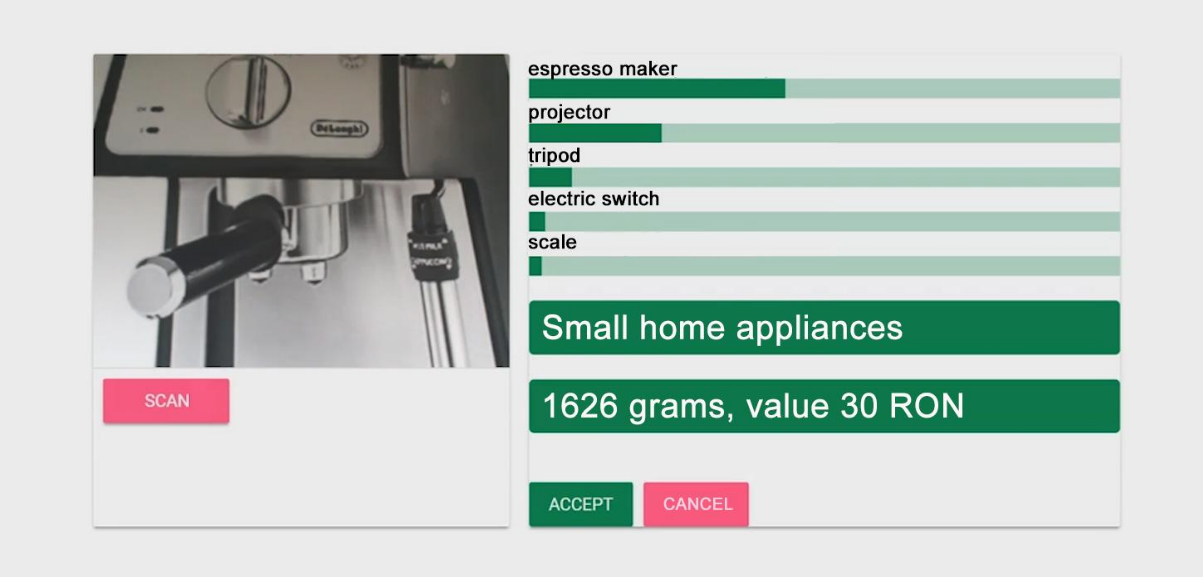

Figure 3. Application interface

THE ELECTRONIC SCALE INTEGRATED ON THE CONVEYOR AND THE READING INTERFACE

The electronic scales are connected via USB and the values provided by them are read through node.js and processed by the web application. The weighing app module has three methods that can be called independently:

Connect () - connects to the driver and if the scales are not immediately online, sets up a listening subroutine until it becomes online. This method is required to access the methods below.

GetWeight () - Get the current weight on the scale. Returns an object that contains the value and unit of measurement (ounces or grams).

GetOverweightStatus () - If the ladder is overweight, this method will return true, otherwise false.

GetStatus () - returns true or false based on the availability of the scale.

Events: Online, Offline, weight-change, overweight-change, weight, end.

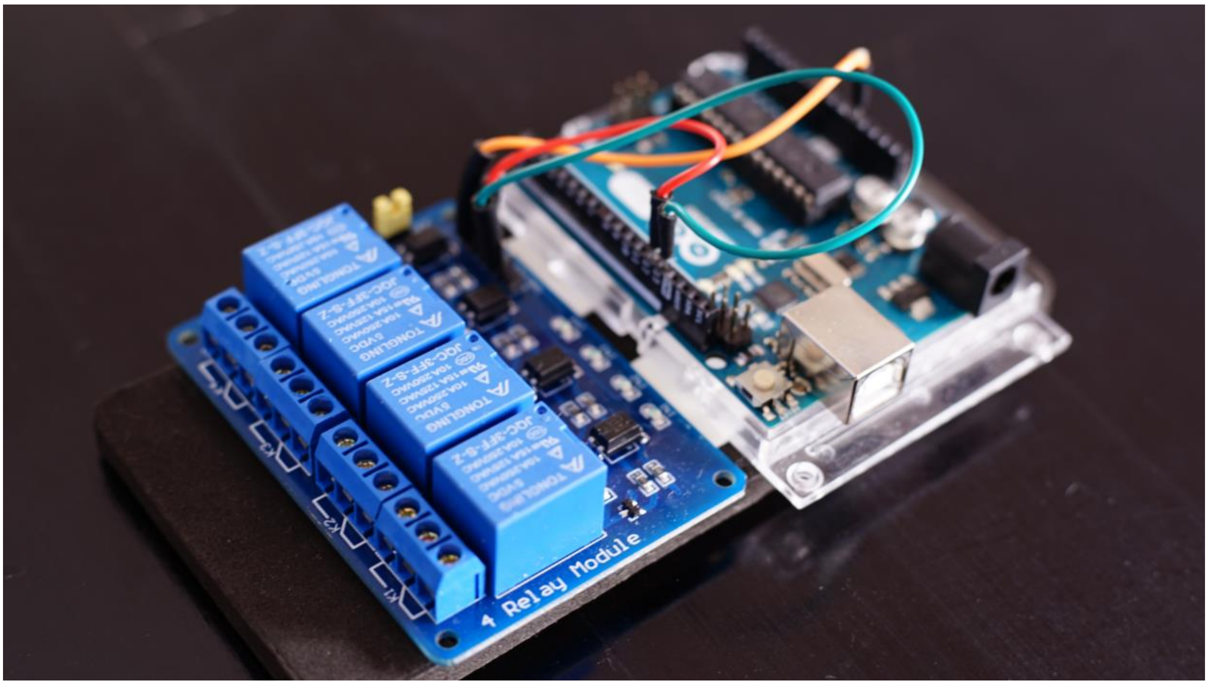

Figure 4. Arduino and relays board

Figure 4 shows the automation hardware prototype consisting of the Arduino development board and the relay block. The relays control the conveyor motors in a timed manner in the two travel directions.

CONCLUSION

The WEEE identification system is mandatory to obtain a full automated WEEE collecting system. The proposed automated WEEE identification system can accurately identify all types of WEEEs because different identification methods are used: visual method, weighting method, metal detection method etc. Preliminary tests on small electrical appliances show good results and the solution of WEEE identification can be validated. The future research will be focused on integration of the WEEE identification system into the automated WEEE collecting system. Tests on electronics, small and large electrical appliances will be made.

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