Intelligent robotic system for urban waste recycling

Konstantia Moirogiorgou, Technical University of Crete, Chania, Crete, Greece, dina@display.tuc.gr
Freiderikos Raptopoulos, Foundation for Research and Technology-Hellas, Heraklion, Crete, Greece, freirapt@ics.forth.gr
George Livanos, Technical University of Crete, Chania, Crete, Greece, glivanos@ics.tuc.gr
Stavros Ofanoudakis, Technical University of Crete, Chania, Crete, Greece, sorfanoudakis@ics.tuc.gr
Maria Papadogiorgaki, Technical University of Crete, Chania, Crete, Greece, mpapadogiorgaki@mlh.tuc.gr
Michalis Zervakis, Technical University of Crete, Chania, Crete, Greece, michalis@display.tuc.gr
Michail Maniadakis, Foundation for Research and Technology Hellas, Heraklion, Crete, Greece, umniada@ics.forth.gr

Abstract—Urban waste management is a most challenging issue for modern societies. Reducing pollution and saving environmental resources provides significant opportunities for local, national and international economic growth. In Greece, the recycling rates are currently low compared to other European countries. The current study proposes an autonomous, intelligent robotic system for categorizing and separating recyclable materials aiming to contribute in increasing the recycling rates in Greece. The system is a series connection of an optical sub-system and a robotic sub-system. The optical sub-system receives input from a ordinary RGB and an NIR camera. These are processed in combination for the identification and categorization of recyclables into predefined material types. The output of the optical sub-system provides a list of potential targets (recyclables) to be picked and sorted. This is forwarded to the robotic sub-system, which undertakes the physical separation of the materials to the appropriate bin. The proposed system, named ANASA system, has been deployed in two different urban waste management industrial units, in DEDISA, Chania, Crete, Greece (processing recyclable wastes) and in ESDAK, Heraklion, Crete, Greece (processing composite wastes), where the system's reliability and validity is experimentally tested in real industrial environments. The advantages over the existing ordinary recycling systems are significant: high reliability in object recognition (material detection), short separation cycle (high speed), significantly low installation volume, low cost and ease of application to both old and new recycling industries. The combination of the above features provides a potential for exploitation as a complete commercial commercialization.

Keywords—image classification, machine learning, NIR spectrum analysis, robotic sorter, waste management

I. INTRODUCTION

The increasing interest in the concept of circular economy for sustainable use of raw materials and the strengthening of recycling policies are key elements of modern and efficient waste management. Regardless of how waste collection and recycling is implemented in each country, collected waste needs to be processed either to remove unwanted or hazardous objects from the main material (negative separation of objects) or, to sort the reusable materials from the partially mixed waste collected (positive separation). Sorting these waste streams is today still performed mainly manually, which is a mind-numbing task.

The use of advanced robotic sorting systems can crucially support the modernization of Industrial Material Recovery Facilities (MRFs) to speed up and automate waste treatment. Along this line, there is an increasing interest for implementing smart and automated waste treatment solutions. To date, optical sorters is the technology that dominates industrial MRF installations. Besides accomplishing 90% purity of recovered materials, this technology performs mainly binary classification of waste streams. The latter means that multiple binary classifiers should be arranged sequentially to separate more material types. To compensate for the above, the interest in the development of recycling systems has recently shifted to the use of robotic waste sorters.

The operation of the robots assumes the ability to visually identify and categorize materials. In recent years, a variety of techniques and approaches have been developed for the detection, and sorting of recyclable material, particularly of widely used polymer types. They concern laboratory methods, or automated techniques, which are either commercially available, or in the research and development phase. Such technologies are mainly based on hyperspectral imaging in order to identify plastic and other materials and increase the quality of recycled products in industrial applications [1], [2], [3]. Hyperspectral imaging is related to spectroscopic methods [4], that cover different regions of the electromagnetic spectrum, such as, X-ray, Raman, laser and infrared [5], [6], [7]. Among them, Near Infrared spectrum ranging from 780 nm to 2500 nm is the technology that is now characterized by the greatest development for application in industry, especially in order to identify the different polymer types [8].

ANASA system upgrades the idea of recyclable waste classification; it proposes an autonomous robotic system for categorizing and separating recyclable materials, based on optical detection and classification, which guides the robot in grasping and physically separating the detected materials (Fig. 1). The methodology proposed in this paper deals with the effective classification of 6 materials, namely 4 polymer types, PET, HDPE, PP, PE-film and 2 others, i.e. aluminum and paper.

![Fig. 1. Schematic representation of proposed robotic system for recyclable waste sorting](image-url)
More specifically, optical data captured by an RGB-D camera are processed in order to provide the information of the ID and position of each detected material. Along with that, the NIR signals of several wastes are offline normalized, in order to extract significant features that allow their efficient discrimination. The NIR information drives the optical sub-system in a supplementary way in order to increase the RGB output accuracy. The optical sub-system output data, i.e. the ID, position and identification accuracy are sent in real-time to the robotic sub-system that is connected in series with the optical sub-system for the pick-and-place operation of the different material types to dedicated bins. The robot can adopt different waste picking policies to improve its performance based on economic and environmental criteria. The novelty of the proposed approach is two-fold:

- although the NIR signals are not filtered for denoising purposes, yet the performance of the calculated features is remarkably high, namely greater than 90%. The rationale behind the usage of the initial non-filtered data, concerns the acceleration of the entire process, since this classification is intended for a real-time application.

- four different waste picking policies are contrasted, showing that the order in which the objects are transferred to the material bin can significantly affect the performance of the composite system.

II. RELATED WORK

Regarding the optical sub-system functionality, currently there are many machine learning algorithms for object detection, but only a few of them fulfill the needs of ANASA system functionality. The YOLO (You only look once) [15] is known for its speed and accuracy and it is used widely in a variety of object detection applications. One of the key characteristics of this algorithm is that it requires only a forward pass through its neural network to detect objects in an image, which affects directly the inference speed. As for the NIR spectra of materials, that are initially captured by means of specialized sensors, the hyperspectral cube containing the spatial, as well as the spectral information of each image pixel is widely used in similar applications [9]. The NIR signals can be processed for normalization and smoothing purposes by applying denoising methods, such us moving average windows, median filters and Savitzky–Golay-based transformations, which are used in order to eliminate the baseline-drift and other noises induced by the industrial layout and special conditions [10], [11]. The consequent signal analysis can be performed by means of methods such as the Fourier Transform Infrared Spectroscopy (FT-IR) [9], for the extraction of significant features, while computational methods of pattern recognition can be exploited to distinguish among the different materials. These methodologies are based on machine learning algorithms and aim to extract unique spectral signatures that characterize the discrete solid wastes and polymers' types, such as PET, HDPE, PS, PP, PC, PVC, ABS, etc. Several algorithms such as Support Vector Machines (SVMs) [10], [8], [12], Principal Component Analysis (PCA) [9], [13], [8], Partial Least Square Discriminant Analysis (PLS-DA) [9], Minimum Distance [14] and k-Nearest Neighbors (k-NN) [12], have been used to achieve recyclable material discrimination and categorization. Additionally, along the same direction, non-linear methods such as Artificial Neural Networks (ANNs) [14] and Self-Organized Maps [14] have been proposed in the literature.

The use of robots for waste separation has been studied for more than a decade [20]. Besides the fact that parallel grippers have been used for recyclable grasping and manipulation, (eg. [21]) the use of vacuum grippers has dominated the field of sorting consumer waste as witnessed by the numerous commercial robots used in the industry (eg. ZenRobotics, AMP Robotics, Sadako, samurAI). Along the same line, we have recently developed a robot that adopts a pick and toss approach to quickly transfer recyclables to material bins [22].

The present work demonstrates that commercial systems can improve their operation by adopting waste collection policies that allow them to meet the individual needs of each MRF.

III. METHODOLOGY

A. Optical sub-system

RGB camera: The YOLO neural network architecture consists of three main parts, the backbone, the neck, and the head. The backbone takes as input the original image and is a feature extractor which consists of a series of convolutional networks that extract the important features from the input images. In our application, we are using as a backbone the Cross Stage Partial Networks (CSP) [16], which was proved to enhance the learning capabilities of many famous neural network architectures. The neck is a Path Aggregation Network (PaNet) [17] which connects the many outputs of the feature extractor with the inputs of the head, which in our case is the YOLO layer [18]. The outputs of the YOLO layer are the final object detections of the input image. For every detected object there is output data about its class (ID), coordinates of the bounding box in the image, and a confidence score.

Additionally to the traditional object detection, we have also implemented the methodology of object tracking [19]. This means that we are exploiting the sequential property of the input data to improve the accuracy of the final results. In detail, every newly detected object is assigned to a unique ID which helps in storing additional information about this object. For every following frame, the list of the already detected objects is compared to the new predictions, by using metrics such as Intersection over Union (IoU), in order to get the newly updated list of detections. This process increases our confidence in the predictions by combining the information of the class and the confidence score over multiple frames, e.g. when an object is detected as plastic for x frames and only for 1 frame in between is detected as metal, we don’t want it to be considered as metal, etc.

Finally, in our implementation, when an object is consistently detected for N frames, where N is proportional to the fps of the camera and the sample rate, we send a message, through a TCP socket, to the robotic sorter so it can be picked and placed into the correct recycling bin. The message that is sent is of the form “class, x_center, y_center, conf, width, height”, where the class is an integer, (x_center and y_center) is the location of the center of the object’s bounding box and (width and height) its dimensions and conf is the confidence score of the detected object. We consider the transfer time of the message to be negligible so the robotic sub-system is the one responsible to timestamp every object at the time of the message delivery, eliminating this way the need for any further synchronization between the two systems.

The RGB camera used in this application provides us with a 1280x720 pixels video feed at 30 frames per second (fps). We found out experimentally, that we can get equally accurate
results by under-sampling this video feed, which is possible because of the sequential property of the data that was mentioned earlier. In our case, we are using only 1/3 of the frames. In this way, we minimize the processing power needed and enable our algorithms to be able to run on even PCs with common CPU. More specifically, our object detection algorithm takes approximately 25 ms to fully process and provide detections for each frame using an NVIDIA RTX 2080 SUPER GPU, which means that we can support real-time video feeds up to 40 fps or even more by under-sampling. For the training purposes of our model, we have assembled a dataset of 1311 images (2300 plastic, 500 metal, and 500 paper labels within these images) with most of them coming directly from the waste recycling plant, as we can see in Fig. 2.

NIR camera: The NIR raw data have been captured using the hyperspectral line-scanning camera SPECIM FX17, with spectral range [935.61 nm - 1720.23 nm], 224 spectral bands and a spatial line sampling of 640 px. The camera and the illumination system were installed above one of the conveyor belts of DEDISA site which is the urban waste management industrial unit of Chania, Crete, Greece. Several videos were captured in order to define specific parameters, such as the optimal frame-rate that corresponds to 90 fps. The derived raw data concern package containers of six waste materials, namely, PET, HDPE, PP, PE-film aluminum and paper. The total number of NIR samples that were utilized for training, test and validation purposes after eliminating the invalid signals, corresponds to 1525000 (Table I). It is important to notice here that the spectrum range of the NIR camera allows to identify the six different waste categories already mentioned, while other waste categories is not possible to be uniquely identified due to their spectral signature that is out of the NIR spectrum range.

The applied methodologies include three consecutive stages: a) pre-processing of NIR signals b) significant feature extraction and c) feature selection and binary multiple classification of NIR spectra. Initially, the NIR signals were pre-processed in order to eliminate the invalid samples containing infinite and/or "not a number" values and normalized in (0 - 1) reflectance scale using the white- and dark-reference data derived by SPECIM camera. The reflectance amplitude of indicative waste samples are illustrated in Fig. 3. As the final classification is intended for use in a real-time application, the NIR signals were not filtered for denoising purposes and the feature extraction process that follows is performed on the original normalized data.

<table>
<thead>
<tr>
<th>No</th>
<th>Class</th>
<th>Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PET</td>
<td>Plastic</td>
</tr>
<tr>
<td>2</td>
<td>PP</td>
<td>414413</td>
</tr>
<tr>
<td>3</td>
<td>HDPE</td>
<td>335823</td>
</tr>
<tr>
<td>4</td>
<td>PE-film</td>
<td>109277</td>
</tr>
<tr>
<td>5</td>
<td>Aluminum</td>
<td>Other</td>
</tr>
<tr>
<td>6</td>
<td>Paper</td>
<td>230402</td>
</tr>
</tbody>
</table>

As for the classification process, the total 18 calculated features, as well as 9 different combinations of them were experimentally tested by setting them as input into the k-NN algorithm [12], taking into account the Euclidean distance of each test sample from the k-closest training ones and classifying it in the class where most of them belong. Regarding the parameter k, it was set to k=1, namely, each sample is simply assigned to the class of the single nearest neighbor. Finally, 10-fold cross validation has been applied in order to derive reliable results. Subsequently, the initial
features set was reduced, based on the k-NN’s highest performance on binary classification’s i.e. 91.26%, where 9 (out of 18) extracted features were selected, see Table II.

<table>
<thead>
<tr>
<th>No</th>
<th>Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1, 2</td>
<td>Mean Value and Standard Deviation</td>
</tr>
<tr>
<td>3</td>
<td>Total Energy</td>
</tr>
<tr>
<td>4, 5, 6</td>
<td>First, Second and Third Principal Component</td>
</tr>
<tr>
<td>7, 8, 9</td>
<td>Wavelength of First, Second and Third Significant Valley</td>
</tr>
</tbody>
</table>

The finally selected features were further evaluated on binary discrimination between the super-classes of plastics and other waste materials, by means of the SVMs algorithm with a linear kernel. In addition, multiple categorization was performed in 6 individual classes of PET, HDPE, PP, PE-film aluminum and paper, using the k-NN and Linear Discriminant Analysis (LDA) methods, leading to an even higher classification accuracy of 95.68%. The entire process of NIR classification is presented in the block diagram of Fig. 4.

![Fig. 4. Description of the materials’ classification based on the NIR spectra](Image)

Fusing the information extracted in the visible (RGB sensor) and Near-Infrared (HSI sensor) electromagnetic spectrum, each object/material detected is assigned a unique label that characterizes the type of polymer it belongs to, the confidence (% percentage) of its prediction accuracy along with its size and position with respect to the conveyor belt.

**B. Robotic subsystem**

Considering the a priori known distance between the two cameras and the fixed speed of the belt it is possible to synchronize the information captured by the two sensors and enable perfect image registration/alignment recorded by the two sources. Towards this procedure and based on the key information extracted, a robotic arm placed beyond the optical system at a predetermined distance is capable of estimating the time and position each detected object will pass under it and grab the “optimal” material for sorting under a selection criterion (e.g. most valuable material to retrieve, easiest object to grab due to size etc).

Given the request for fast repetitive actions in waste sorting tasks, the implementation of the robotic subsystem is based on the ABB IRB360 delta robot. It consists of three high-torque servomotors that are mounted on a rigid frame. On each motor shaft, an arm is mounted perpendicular to the shaft’s rotational axis. These arms are connected to lightweight linking rods arranged in parallelograms to restrict twisting motion. The joints at both ends of each parallel rod move freely, typically in ball joints. The three arms are connected to a central platform that hosts the end effector. This is implemented as which enables picking, holding and releasing the recyclables as they are transferred to material-specific bins. The vacuum gripping system consists of (i) a flexible and compliant suction cup that pathetically adjusts its shape to the unstructured surface of the individual recyclables (ii) a blower used to generate high flow vacuum capable to pick and hold the selected materials (iii) a custom-made shock absorber moved along the z axis that is used to gradually press the suction cup on the material to facilitate sealing.

The sorting of recyclables assumes the optical system to guide the operation of the robot for the physical separation of objects. Accordingly, as soon as an object is identified and categorized, the optical system provides the robot the 3D location, the material type and the time that the given object was recognized. The flow of the messages is continuous and uninterrupted and is implemented through an ordinary TCP-IP link. At the other end, the robot develops and maintains a list of all recognized recyclables.

A speed sensor attached to the conveyor belt is used to provide in real-time the speed of recyclables (located on the belt). The robot keeps track of the current location of the objects using the speed of the belt and the time each object has been recognized by the optical system. In that way, the objects that enter or leave the workspace of the robot can be easily inferred. Any object entering the workspace of the robot is a potential target for selection and separation. We assume \( P_i = (x_i, y_i, z_i) \) being the location of the robot and \( P_r = (x_r, y_r, z_r) \) being the current location of the target. If the given object is selected for sorting, the robot will move towards the moving object to pick it at location \( P_{pick} = (x_{pick}, y_{pick}, z_{pick}) \) which is estimated by the following equation:

\[
x_{pick} = x_0 + \int_0^{t_{All}} v_x(t) dt \\
y_{pick} = y_1 \\
z_{pick} = z_t
\]

(1)

Where \( t_{All} = t_{hor} + t_{ver} \) is the total time of robot motion, with \( t_{hor} \) being the duration of the horizontal displacement and \( t_{ver} \) is the time of the vertical movement of the robot. In the current implementation, the vertical motion profile of the robot follows a predefined configuration with known implementation time. For the horizontal displacement we assume that the robot moves at a constant acceleration \( a_r \).

The horizontal distance to be covered by the robot is estimated as \( D = \sqrt{(x_{pick} - x_0)^2 + (y_{pick} - y_0)^2} \). We assume that the robot moves at a constant acceleration \( a_r \).

Following the industrial specification of the motion profile of the robot which uses the constant \( C_{ref} \), the time of horizontal movement is specified as \( t_{hor} = \frac{C_{ref}D}{a_r} \).

By combining the above equations, we come up with a complex differential equation that is not trivial to be solved. We use the Newton’s iterative method to obtain an approximate solution of the differential equation, which provides with the time to be spent and the 3D location that the robot will be able to pick the given material. The above procedure is applied for all potential targets \( i \), located within the workspace of the robot to obtain a list of reaching times \( t_{All}(i) \), for all reachable materials.
In the current implementation we consider how the market-value of material \( v_m(i) \), for each material type \( m \) can have a role in prioritizing the order that recyclables are sorted. We assume the same market value of all items of a given material type (i.e., \( v_m(i) = v_m \), irrespective of the size of item \( i \)).

Then, we combine the time to reach the \( i \)-th item \( t_{all}(i) \) with the market-value of the given material \( v_m(i) \) to come up with a new “value-in-time” measure described by the equation:

\[
vt_p(i) = v_m(i) \left( 1 + t_{all}(i) \right)
\]

where the power-parameter \( p \) gives the opportunity to easily balance between the importance of market-value and processing time. Additionally, it is noted that time is measured in milliseconds, being typically in the range of 250-500ms. Following the above, any time the robot needs to choose among all reachable items \( i \), a new recyclable item \( i^* \) to sort, we solve the following optimization problem:

Find \( i^* \): \( vt_p(i^*) \geq vt_p(i) \), for all reachable items \( i \)

IV. RESULTS

In Table III, we present the evaluation of our test set which consists of 400 images that were not used for training. We can see that our model has detected correctly 85% of the plastics while 13% were not detected at all (False Negatives). Furthermore, the model had 83% accuracy for the metals with 8% split to the two other classes and 9% false negatives. As for the paper class, 71% of the objects were correctly detected, while 20% were FN. We can see that 73% of the false positives belong to the plastic class, while 22% belong to the paper class and only 6% belong to the metal class. Finally, the total precision of the model is 86% which means that only 14% of the predictions were false positives, while the total Recall is 76% showing that only 24% of the predictions were false negatives. The detection accuracy is planned to be improved by extending the training set of the models with more real-life images in all categories of waste.

<table>
<thead>
<tr>
<th>Actual labels</th>
<th>Plastic</th>
<th>Metal</th>
<th>Paper</th>
<th>Background FP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plastic</td>
<td>0.85</td>
<td>0.05</td>
<td>0.08</td>
<td>0.73</td>
</tr>
<tr>
<td>Metal</td>
<td>0.01</td>
<td>0.83</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>Paper</td>
<td>0.01</td>
<td>0.03</td>
<td>0.71</td>
<td>0.22</td>
</tr>
<tr>
<td>Background FN</td>
<td>0.13</td>
<td>0.09</td>
<td>0.20</td>
<td></td>
</tr>
</tbody>
</table>

TABLE III. CONFUSION MATRIX - EVALUATION OF THE TEST SET

Regarding the NIR spectra, several classification experiments have been conducted using different machine learning techniques, in order to test and validate the finally selected features. The results were evaluated in terms of particular performance metrics, namely the per class accuracy - ACC, precision (Positive Predictive Value) - PR, sensitivity (recall) - SEN and specificity - SPE (Table III), where TP, FP, TN, FN stand for true positive, false positive, true negative and false negative samples respectively, for each class.

More specifically, the 9 finally selected features (Table II) were fed as input to the SVM algorithm in order to compare its performance to the previously applied k-NN on binary classification concerning the super-categories of plastics and other wastes. Apart from of being far faster in execution, the k-NN application led to considerably higher results in terms accuracy, namely 91.34% over SVM’s 63.97%.

Furthermore, computer simulations were performed in order to classify the signals among the 6 individual waste categories (i.e. PET, HDPE, PP, PE-film, aluminum and paper), while the results were derived upon 10-fold cross validation by means of LDA and k-NN. The k-NN method slightly outperformed LDA yielding an average classification accuracy of 95.68% over LDA’s 94.17%. The detailed average results of the other statistical metrics concerning the k-NN’s performance on binary and multiple classification using the entire initial and the finally reduced set of features, are depicted in Table IV.

<table>
<thead>
<tr>
<th>Evaluation Metrics</th>
<th>Binary</th>
<th>Multiple</th>
<th>Binary</th>
<th>Multiple</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy</strong></td>
<td>0.79</td>
<td>0.73</td>
<td>0.81</td>
<td>0.91</td>
</tr>
<tr>
<td><strong>Precision</strong></td>
<td>0.84</td>
<td>0.71</td>
<td>0.92</td>
<td>0.91</td>
</tr>
<tr>
<td><strong>Sensitivity</strong></td>
<td>0.83</td>
<td>0.85</td>
<td>0.91</td>
<td>0.91</td>
</tr>
<tr>
<td><strong>Specificity</strong></td>
<td>0.78</td>
<td>0.89</td>
<td>0.94</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Finally, it should be mentioned that the illumination system greatly influences the captured NIR raw data, since the light intensity is shown to be proportional to the reflectance range of the NIR spectrum of each material. Based on our experiments, it was demonstrated that poor lighting conditions lead to weak signals, as opposed to increased illumination, which improves the classification results, allowing the effective discrimination among the different materials.

As for the optical subsystem, it has been integrated with the robotic unit to create a robotic sorter of recyclable waste operating in demanding industrial environments. A screenshot of the industrial setup at DEDISA site is presented in Fig. 5, while the operation of the overall system is shown in this video link: https://youtu.be/6dV4vg3EeqU.

Fig. 5. Proposed system established in fully industrial conditions

Moreover, the current work examines how the productivity of the system changes when adopting different optimization criteria for selecting the material to sort. We examined four approaches: (i) select targets in the order they are identified by the optical system (ii) select the material with the shortest reaching time (\( p = 0, \) in eq. (2)), (iii) select the material with the best ratio of commercial value to reaching time (\( p = 1, \) in eq. (2)) (iii) select the material with the best ratio of squared commercial value to reaching time (\( p = 2, \) in eq. (2)).
To evaluate the different selection approaches we used a predefined set of 1000 different waste items consisting of 400 plastics, 300 papers and 300 metals. In each experiment, all items pass through a trommel to fall onto a conveyor belt, in random order. To reduce the chance of a random distribution of materials on the belt favoring one of the material selection approaches, we perform 4 different experimental sessions for each approach.

The aggregate results for the benchmarking of the four different material selection approaches are shown in Table V. The first approach is the least efficient as it achieves a low number of recovered pieces and a low commercial value of the recovered material. This is because very often the robot needs to retrieve materials at the edge of going out of its scope, thus traveling long distances. The second approach considers only the time it takes to reach candidate targets, to select the shortest one. In this case the number of items recovered is the highest, but without achieving a high profit. The third approach, which examines the ratio between commercial value and reach time, achieves the highest profit over all examined approaches, although the number of items recovered is slightly lower than the second approach. Finally, in the fourth case where even more emphasis is placed on the commercial value, the overall economic result achieved is not high enough as the number of items recovered is reduced.

Overall, based on the results of Table V, the approach with the maximum environmental impact is the second, while the one that enhances the profitability and sustainability of the material recovery facilities is the third.

Table V. Average Performance of the Robotic Recyclable Sorter in Four Experimental Sessions

<table>
<thead>
<tr>
<th>Item selection</th>
<th>Recovered Materials</th>
<th>Market Value</th>
<th>Number of items</th>
</tr>
</thead>
<tbody>
<tr>
<td>approach</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First-in-first-out</td>
<td>6.33</td>
<td>853</td>
<td></td>
</tr>
<tr>
<td>Value in time, (p=0)</td>
<td>6.65</td>
<td>952</td>
<td></td>
</tr>
<tr>
<td>Value in time, (p=1)</td>
<td>7.08</td>
<td>914</td>
<td></td>
</tr>
<tr>
<td>Value in time, (p=2)</td>
<td>6.73</td>
<td>876</td>
<td></td>
</tr>
</tbody>
</table>

V. CONCLUSIONS AND FUTURE WORK

The current work integrates state of the art computer vision, spectral imaging and robotics to develop a complete and effective stand-alone waste sorting system that operates in demanding industrial setups. The theoretical ability of the system to treat all different types of waste, working long hours in harsh conditions facilitates modern environmental policies aimed at (i) managing waste in an environmentally sound manner, (ii) recovering and exploiting secondary materials to reduce the need of primary resources, and (iii) stimulating waste recycling and promoting circular economy activities for the benefit of society and economic development.

The long-term operation of the entire system in hard industrial conditions will guide the focused adjustment of the robotic waste sorter parameters to achieve optimal performance and excellent waste separation results.

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