New Waste Beverage Cans Identification Method

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***Abstract*— The primary emphasis of this work is on the development of a new waste beverage cans identification method for automated beverage cans sorting systems known as the SVS system. The method described involved window-based subdivision of the image into X-cells, construction of X-candidate template for N-cells, calculation of matching scores of reference templates for the N-cells image, and application of matching score to identify the grade of the object. The SVS system performance for correct beverage cans grade identification is 95.17% with estimated throughput of 21,600 objects per hour with a conveyor belt width of 18″. The weight of the throughput depends on the size and type of the objects**.

***Index Terms*— Identification, SVS, beverage cans, sorting system**

I. INTRODUCTION

Computer vision (CV) deals with extracting meaningful descriptions of physical objects from images (Ballard & Brown 1982, Brosnan & Da-WenSun 2003, and Kulkarni 2001). Due to low cost powerful solutions, the applications of CV have increased tremendously in diverse fields such as medical diagnostic imaging, food industry for quality evaluation, factory automation, robot vision, object identification, military reconnaissance, remote sensing, mineral exploration, cartography, and automated object grading and sorting. The aim of this motivation is to realize the necessity of the automated solid waste sorting system and justify the development of a smart vision sensing (SVS) system for automated recyclable waste beverage cans sorting using state-of-the-art of the CV.

The primary challenge in the recycling of beverage cans is to obtain raw material with the highest purity. In recycling, highly sorted stream facilitates high quality end product, and save processing chemicals and energy because various grades of beverage cans are subjected to different recycling processes. In addition, the amount of sludge and rejects generated in recycling processes is decreased for the utilization of sorted object in recycling as well as reduces the amount of energy needed to produce recycled cans. In this work, the type of a beverage cans is based on weight, color, usage, raw material or a combination of these factors.

Automated sorting systems are classified into mechanical and optical systems. Since 1932 to 2009, different mechanical and optical sorting methods have been developed to fill the demand of object sorting. Mechanical sorting cannot achieve commercially viable throughputs and accuracy. The popularity of optical sorting systems has increased because of inadequate throughput of mechanical sorting systems. The greatest advantages of optical sorting systems include the following: consistent and reliable production efficiency with a relatively high hit rate and purity; and low operational cost because of fewer manual workers on the production line.

The main objective of the research is to develop a smart vision sensing (SVS) system for automatic recyclable waste beverage cans sorting. More specifically, the aims is To select the best features and classifier for the smart vision sensing (SVS) system for automatic recyclable solid waste sorting.

II. THE SVS SYSTEM FOR SOLID WASTE SORTING

Figure 1 illustrates the block diagram of the proposed intelligent computer vision system for automatic sorting of recyclable beverage cans and a picture of the actual systems. The computer vision process consists of three parts: perception, cognition and action. The perception or image acquisition portion of this vision system consists of a commercially available webcam and a special lighting arrangement. The main responsibility of the action component of the vision system is to segregate waste beverage cans into different types based on the command of the cognition part of the vision system. Mechanical system are used to segregate and to pile different type of object according to their respective waste bins. In this research, we emphasize a beverage cans type identification system, which covers the perception and cognition components of the proposed system.

In this proposed system, 640×480 RGB images are captured from inspection zone on the conveyor belt by using Logitech QuickCam Pro 4000 Web Camera [46], [47]. The specifications of the webcam are CCD Optical sensor, color Camera, CCD Image Sensor Lens Construction support Manual **Focus** Adjustment, 4 pin USB Type A Interface for

USB Expansion / Connectivity with Computer Interface. In webcam properties setting, the brightness, contrast and saturation are adjusted at 50%, 50% and 100% of their respective scales.

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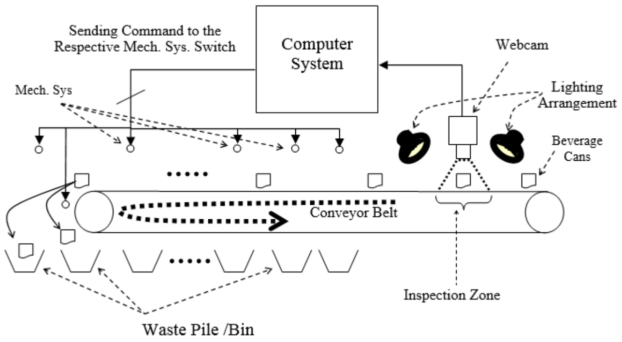

Figure 1 Block diagram of the intelligent computer vision system for automatic sorting of Beverage Cans

In this experiment, it is observed that the performance of the vision system is extremely influenced by the lighting arrangement. For calibration and adjusting the lighting, three different lighting techniques namely front lighting-directional-bright field illumination, front lighting-directional- dark field illumination, and diffuse front lighting are considered in this research as shown in Figure 2. In both front lighting-directional-bright field illumination and diffuse front lighting, the images from the inspection zone show some reflection problems such that the object on the conveyor. Moreover, the reflection from the surface of the object is not uniform. It is important that the texture information of the objects is analyzed. Even one object of the same color in whole body showed different color combination in histogram analysis of the segmented portions of the image due to non-uniform lighting. In front lighting-directional-darkfield illumination, image from inspection zone is distinctive for texture analysis and the object surface is illuminated uniformly. Moreover, front lighting-directional-darkfield illumination is widely used in surface scratches or texture analysis (Pham D.T., & Alcock, R. J., 2003; Burke M.W., 1996), thus, this illumination technique is adopted for this experiment.

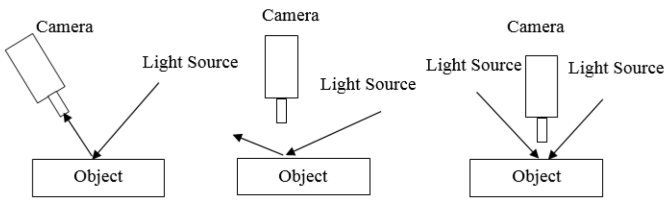

Figure 2: Lighting Techniques: (a) brightfield illumination, (b) darkfield illumination and (c) diffuse frontlighting

III. Feature Extraction

In the feature extraction phase, both color and gray scale images are considered. Brunner et al. (Brunner, C. C., Maristany, A. G., Butler, D.A., Leeuwen D.V., & Funck, J.W., 1992) converted the usual RGB color space into other potentially more useful color spaces, but they found that none provided any improvement over RGB. Thus, the RGB color space is considered in this research. For color images, each of the three color components – red, green and blue – are considered separately. For gray scale image, standard grayscale transformation is obtained from the original RGB image. Identification is primarily based on the dominating color level of the objects. In the feature selection process, special emphasis is placed on those features, which provides significant information regarding the dominant color level. Initially, seventeen first order features, such as mean, standard deviation, skewness, kurtosis, dispersion, lowest color level, highest color level, mode of the color level, entropy, energy, lower quartile, upper quartile, histogram tail length on dark side, histogram tail length on light side, median color level, range of the color level, and inter-quartile range, are extracted from the image using equations to determine the significant features in identification.

To calculate the first order features, the gray level histogram of the image is calculated first. The histogram, h(x), is a one dimensional array that represents the number of pixels in the image with a gray level of x. The x parameter can take any value between 0 and Z-1, where Z is the number of gray levels in the image. For color images, three histograms are calculated for the three color components: red, green and blue.

$$\text{Mean, } \mu = \frac{\sum_{x=0}^{Z-1} h(x)}{Z} \qquad [1]$$

$$\text{Standard Deviation, } \sigma = \sqrt{\frac{\sum_{x=0}^{Z-1} (h(x)-\mu)^2}{Z}} \qquad [2]$$

$$Skewness = \frac{\sum_{x=0}^{Z-1} (h(x)-\mu)^3}{Z\sigma^3} \qquad [3]$$

$$Kurtosis = \frac{\sum_{x=0}^{Z-1} (h(x)-\mu)^4}{Z\sigma^4} \qquad [4]$$

$$Dispersion = \sum_{x=0}^{Z-1} \left| h(x)-\mu \right| \qquad [5]$$

lowest color level, $c = x \,|\, h(x) \neq 0$

where $0 \leq x < Z$ and $h(i) = 0\ \forall i: 0 \leq i < x$

highest color level, $d = x \,|\, h(x) \neq 0$

where $0 \leq x < Z$ and $h(i) = 0\ \forall i: x < i < Z$

$$Mode = x \,|\, h(x) > h(i): \forall i, 0 \leq i, x < Z, i \neq x \qquad [6]$$

$$Entropy = \frac{\sum_{x=LowerLimit}^{UpperLimit} h(x).\log_2(h(x))}{tpixelsp} \qquad [7]$$

Where *tpixelsp* is the total number of pixels used to calculate entropy

$$Energy = \frac{\sum_{x=LowerLimit}^{UpperLimit} x^2.h(x)}{tpixelsg} \qquad [8]$$

where *tpixelsg* is the total number of pixels used to calculate energy

IV. Result and Discussion

Since no databank was available for beverage cans identification system following our method of image extraction, we had to create a database of the objects. One of the tasks to be studied for the enrollment process is the color value of background that forms the ranges of different grades. It is obvious that the bigger the number of samples used, the more accurate range of color for respective grade of object will be created. 20 samples are considered sufficient to create accurate range of color for respective types of beverage cans. We have collected 3 photographs with resolution 100 dpi (dot per inch), 200 dpi, and 300 dpi for each of 160 objects.

In order to develop the proposed system, the software tools Matlab 7.4 for front-end application, Microsoft Access 2000 for backend database support, and MS Excel 2000 for data sheets and experimental results analysis are used.

The three types of waste beverage cans, Aluminum (ABC), Non-Aluminum (NAC) and Non-Recyclable (NRC), were considered in this experiment because of their dominating role in waste object with 1500 samples. Different templates were created for the same grade of object. Ten samples were considered to create an accurate feature vector for the reference template object grade.

In this section, a relative comparison is made based on the outcomes of the proposed method for ABC, NAC and NRC. The images P(a), Q(a) and R(a) represent the original images of ABC, NAC and NRC with background noise; in addition, the images P(b), Q(b) and R(b) represent the preprocessed images of ABC, NAC and NRC, respectively. The calculated first order features of the ABC, NAC and NRC are illustrated in Figure 3. The discriminating capabilities of the significant feature energy, mode, and histogram tail length on the dark side, histogram tail length on the light side, lower quartile, and upper quartile are illustrated in Figure 4.

The success rates of the object grade identification process for absolute distance metrics at different values of K are tabulated in Table 1. The correct identification rate is calculated based on the percentage of the number of objects that are classified into their respective object grades. Using the absolute distance metric with KNN, the results are 90% and 93% for k=3 and k=5, respectively.

Grade: WP PG Comments: NAC
PgID: 50

	BLUE	GREEN	RED	GRAY
1. Mean Value	108.8125	108.8125	108.812	108.812
2. Standard Deviation	457.53760	250.58589	280.367	269.1531
3. Skewness	10.986167	3.9906475	3.40455	2.77838
4. Kurtosis	147.08243	6.1452799	14.6290	6.94872
5. Dispersion	44764.75	41651.25	43738.6	43492.6
6. Entropy	10	9.1830284	9.49797	9.414771
7. Energy	59658	53443	57465	56815
8. Lower quartile (a)	236	223	231	230
9. Upper Quartile (b)	254	239	248	247
10. Lowest Color Level (c)	66	84	82	66
11. Highest Color Level (d)	255	255	255	255
12. Histogram tail length on dark side (e)	170	139	149	164
13. Histogram tail length on light side (f)	1	16	7	8
14. Median Color Level (g)	8	12	9	9
15. Range of Color Level (h)	189	171	173	189
16. Inter-Quartile Range (i)	18	16	17	17
17. Mode Gray or Color Level (j)	255	234	255	249

Grade: DNP PG Comments: ABC
PgID: 150

	BLUE	GREEN	RED	GRAY
1. Mean Value	104.58984	104.58984	104.589	104.589
2. Standard Deviation	215.02861	239.11215	237.2471	233.725
3. Skewness	2.3865506	4.1821378	2.73570	2.68184
4. Kurtosis	4.7053834	7.0256573	6.65998	6.30488
5. Dispersion	37202.656	38238.554	38397.7	38189.7
6. Entropy	9.0240659	9.0334707	9.02406	9.00944
7. Energy	35437	30925	33908	33410
8. Lower quartile (a)	178	168	177	175
9. Upper Quartile (b)	197	183	192	190
10. Lowest Color Level (c)	68	70	67	68
11. Highest Color Level (d)	253	246	247	249
12. Histogram tail length on dark side (e)	110	98	110	107
13. Histogram tail length on light side (f)	56	63	55	59
14. Median Color Level (g)	33	32	32	35
15. Range of Color Level (h)	185	176	180	181
16. Inter-Quartile Range (i)	15	15	15	15
17. Mode Gray or Color Level (j)	188	176	184	184

Figure 3 First order feature values

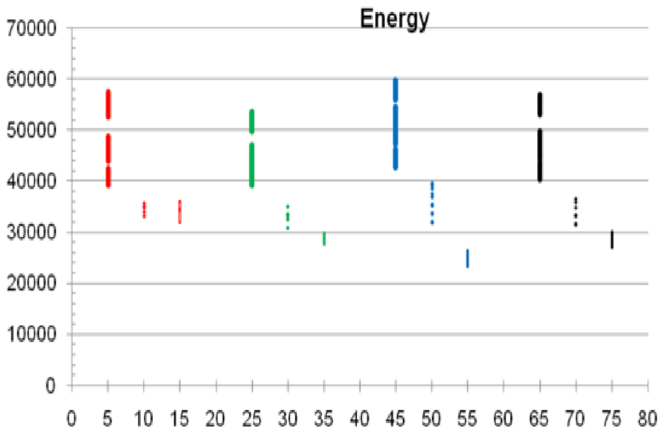

Figure 4. Energy

Table 1 Identification success rate for the two distance metrics at different values of K

Method	K Value	Name of the Distance Metrics	Correct Identification Rate
K-nearest neighbor (KNN)	3	Absolute Distance	90%
	5	Absolute Distance	93%

Finally, the best results of the SVS system is compared with the results published in literature other methods shown in Table 2. It is observed that the performance of the SVS system is the best among all existing systems. The template matching method showed the closest performance. The average maximum classification success rate of the template matching system is 94.67%, while the SVS system offered 95.17% classification success rate. In real time implementation, the SVS system is more effective and convenient than the template matching technique with regards to computational time and lighting consistency.

For instance, in template matching, significant time is allocated for preprocessing, while in the SVS system preprocessing is not required. Additionally, performance of the template matching method depends on lighting consistency during the enrollment and identification phases. With the SVS system, the lighting dependency has been alleviated because the system uses different reference templates for the same beverage cans types which are taken in different lighting conditions.

Thirdly, for template matching, a 5×5 template consists of 25 pixels; and for each pixel the RGB string length is 4 to 16. The RGB string length for 5×5 template is thus 100 to 400. As a consequence, there are 100 to 400 comparisons between one reference template and one cell image template, which makes the system inconvenient for real time implementation. For the SVS system, the template consists of only two values, namely mode and energy of the RGB components, which greatly improves the speed of the matching process.

TABLE 2. The results of the proposed method are compared with results published in literature

Name Industry Standard	Techniques Applied for Identification	Types of Sensor	Features	Classification Success Rate
Template Matching	Template Matching	Logitech QuickCam Pro 4000 Web Camera	RGB String	94.67%
Co-occurrence Features	Rule based Classifier	Logitech QuickCam Pro 4000 Web Camera	Energy for the Co-occurrence matrices	90.67%
TiTech Systems	Not Mentioned	NIR, CMYK sensor and color camera	Materials, shape, color , texture, and four color printing	80%
MSS Systems	Not Mentioned	NIR, Color sensor, Gloss, and Lignin	The sensor measures the intensity of the material's fluorescence at a specific wavelength in the ultraviolet light.	80%
Mechatronic Design of a Waste Paper Sorting System for Efficient Recycling [41]	Artificial Neural Network	**Four Sensors: Lignin, Gloss, Stiffness, and Nikon D50 Digital SLR camera as a Color.**	**(i) Average Lignin value, (ii) Gloss meter reading, (iii) Deflection in the upward direction, (iv) Deflection in the downward direction, (v) color variance parameter I, (vi) color variance parameter II.**	36.6%
	Fuzzy Inference System Algorithm			90.4%
The SVS System	Window-based subdivision, and Distance Vector with threshold based rules	Logitech QuickCam Pro 4000 Web Camera	Mode and Energy of the RGB Components	95.17%

V. CONCLUSION

The primary emphasis of this work is on the development of a new waste beverage cans identification method for automated beverage cans sorting systems known as the SVS system.

Another important idea that has been implemented is the adaptability to new subcategories of the primary Object grades. The wide range of subcategories of object grades is used to train the system to recognize new subcategories, and as a result the system is scalable and able to provide robust decisions for object identification tasks. Besides, the method was trained with many reference templates using different lighting conditions, which overcame the need to maintain lighting consistency during enrollment and identification phases.

The most important point addressed in this work is that the method, which uses computer vision, can be implemented easily to sort multiple types of beverage cans. Moreover, the algorithm provides robust and fast results because the proposed method avoids the extra computational burden for preprocessing since only two features, mode and energy, of the RGB components are used to identify the dominating color value of the object image. The proposed method can identify three major beverage cans types, ABC, NAC and NRC.

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