A Cans Waste Classification System Based on RGB Images Using Different Distances of K-Means Clustering

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Abstract

This study aims to build a classify the cans waste based on the pixel of captured Red, Green, and Blue (RGB) image by implement different metric 3 distances of k-means clustering; Manhattan, Euclidean, and Minkowski metric distance. The image capturing is designed using combinations of two the conveyor belt speeds of 0.181 m/sec and 0.086 m/sec, two the lightings of halogen and incandescent lamps, and four lighting angles of 300, 450, 600, and 900. The classification results note that the implementation of Manhattan distance on the k-means clustering method for classifying the cans waste into three can types has the highest level of accuracy in the majority of data. The highest accuracy level of classification is obtained from data of captured image on the conveyor belt speeds of 0.181 m/sec, the lightings of halogen lamp, and the lighting angles of 450 by implementing the Euclidean distance, while the lowest accuracy level of classification is obtained from data of captured image on the lighting angles of 300 with the same speeds and the lamp by implementing the Manhattan distance. The highest average accuracy is obtained by implementing the Euclidean distance, that derived from the average accuracy at lighting angle of 450.

Keywords:

I. INTRODUCTION

IN a technology that applies automation systems such as sorting systems in the recycling industry, a classification system is needed in the identification process. A classification system for cans waste types based on Red, Green, and Blue colors (RGB) image pixel has been developed by Resti [1], Resti et al [2] and Yani et al [3-4]. They built the system based on the capture of RGB images from cans placed on a static conveyor belt and room lighting. The classification methods they use are naive Bayes, k-NN and multinomial regression.

The k-mean clustering method is one of the essential methods for grouping (classification) objects into desired k-groups. Some studies that have recently applied this method are Perez-Ortega et al [5], Di & Gou [6], Franti & Sieranoja [7], Kumar & Kaur [8], and Bansal et al [9]. This K-means clustering method determine the distance between each data point and the center of the cluster (centroid) that corresponds using a metric size. The metric size that is often used (as default) to calculate the distance is Euclidean [6, 8, 9]. Besides Euclidean, other metric distances can also be used such as Manhattan, Chebychev, and Minkowski distance [10 -14]

In this study, a can classification system was built based on RGB image capture of cans placed on a conveyor belt with the certain speeds, lighting sources, and lighting angles. The classification method used is k-means clustering with 3 different metric distances; Euclidean, Manhattan, and Minkowski.

II. MATERIALS AND METHODS

This cans waste classification system based on RGB images is designed using combinations of two the conveyor belt speeds of 0.181 m/sec and 0.086 m/sec, two the lightings of halogen and incandescent lamps which are mounted with a certain angle. Four the lighting angles in this capturing system are 30^0, 45^0, 60^0, and 90^0. Suppose $X_{1i}, X_{2i}, \cdots X_{9i}$ are input variables that represent the pixel of red, green, and blue colors successively of the i -th cans image captured at the top, down, and side poses respectively. The nine input variables each have a centroid for each type of j-can that is denoted by $X_{1j}, X_{2j}, \cdots, X_{9j}$. The method starts by selecting k random data points (cans images in pixel) as the initial centroids. The i -th can image in pixel will be grouped into the j -th can type if it has the smallest $D(i,j)$, where the metric distance from the i -th can waste to the centroid of the j -can waste type defined as,

$$D(i,j) = \left| X_{1i} - X_{1j} \right| + \left| X_{2i} - X_{2j} \right| + \cdots + \left| X_{ki} - X_{kj} \right| \quad (1)$$

or

$$D(i,j) = \sqrt{(X_{1i} - X_{1j})^2 + (X_{2i} - X_{2j})^2 + \cdots + (X_{ki} - X_{kj})^2} \quad (2)$$

or

$$D(i,j) = \sqrt[p]{|X_{1i} - X_{1j}|^p + |X_{2i} - X_{2j}|^p + \cdots + |X_{ki} - X_{kj}|^p} \quad (3)$$

Equations (1) - (3) are referred to respectively as the Manhattan, Euclid, and Minkowski distances, where the Minkowski distance is a generalization of both the Euclidean distance and the Manhattan distance. The centroid is then updated by recalculating it as the average of all data points specified in each cluster. These calculations are repeated until no further improvement is obtained (convergence). For each metric distance in this study, k initial centroid was randomly selected from all cans waste data, where k is the number of can types.

III. Results and Discussions

The process of classification the cans waste based on the RGB images into 3 types: tin plate, aluminum, and aerosol cans using three metric distances as formulated in (1) - (3) is done with the help of R programming language and R Studio software. Table 1 - Table 7 only shows results for conveyor belt speeds of 0.086m / s and lighting angle of 45^0. The initial centroid randomly selected for each variable and can type is given in Table 1.

Table 1. The Initial Centroids are selected randomly for each variable and can type

cans type (j -th)	Input variable								
	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}	X_{6i}	X_{7i}	X_{8i}	X_{9i}
1	161.97	161.39	159.77	164.80	164.30	161.58	162.90	162.06	159.89
2	156.89	156.62	156.48	161.15	160.77	160.96	158.77	156.57	157.64
3	155.31	155.83	155.48	159.36	155.83	160.39	159.36	159.48	160.14

The majority of initial centroids in the 1st can type are larger than centroids in the other can type. In both the 1st and 2nd can type, the input variable that has the largest initial centroid is X_{4i} while the input variable that has the smallest initial centroid is X_{3i}. Unlike the two can types, in the 3rd can type, the input variable that has the largest initial centroid is X_{6i}, while the input variable that has the smallest initial centroid is X_{1i}.

The data in Table 1 is used to calculate the distance of the metric in (1) - (3) and then results of the initial classification are obtained. Thus, the new centroid for each variable and cans type is calculated from the results of this initial grouping. This new centroid is the average of all cans. The centroid base on (1) - (3) and is shown in Table 2 - Table 4.

Table 2. The New Centroids base on Manhattan distance

cans type (j -th)	Input variable								
	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}	X_{6i}	X_{7i}	X_{8i}	X_{9i}
1	165.32	165.22	167.28	166.02	165.98	167.54	164.30	164.01	165.46
2	158.97	158.92	159.38	160.27	160.09	160.45	157.18	156.77	156.94
3	154.36	153.21	152.63	154.43	153.94	153.21	151.64	151.08	149.94

Like the initial centroid, for the Manhattan distance, both the 1st and 2nd can types have the largest new centroid in the same variable but not the variable X_{4i} but the variable X_{6i}, as well as the smallest centroid but not the variable X_{3i} but the variable X_{8i}. In the 3rd can type, the input variable that has the largest new centroid is X_{4i} while the smallest new centroid is X_{8i}. The majority of new centroids base on Manhattan distance in the 1st can type are larger than new centroids in the other can type.

Table 3. The New Centroids base on Euclidean distance

cans type (j -th)	Input variable								
	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}	X_{6i}	X_{7i}	X_{8i}	X_{9i}
1	165.42	165.76	167.49	165.02	165.09	166.04	162.66	162.34	163.25
2	158.10	158.14	158.22	159.27	159.23	159.54	156.29	155.94	156.03
3	152.72	150.51	150.42	154.44	153.34	152.78	151.80	151.01	149.97

For Euclidean distance, all of the new centroid in the 1st can type as shown in Table 3 are the largest, while all of the new centroid in the 3rd can type as shown in Table 3 are the smallest. In each of can type, the input variables that have the largest new centroid successively are X_{3i}, X_{6i}, X_{4i} while the input variables that have the smallest new centroid are X_{8i}, X_{8i}, X_{3i}.

Table 4. The New Centroids base on Minkowski distance

cans type (j-th)	Input variable								
	X_{1i}	X_{2i}	X_{3i}	X_{4i}	X_{5i}	X_{6i}	X_{7i}	X_{8i}	X_{9i}
1	166.34	167.17	169.38	164.79	165.08	166.42	162.16	162.01	163.23
2	158.26	158.12	158.14	159.83	159.71	159.92	157.00	156.58	156.60
3	152.87	150.70	150.54	154.51	153.46	152.85	151.88	151.14	150.07

As with the new centroids based on the Euclidean distance metric, in Table 4 it can be seen that all of the new centroid in the 1st can type are the largest, while all of the new centroid in the 3rd can type are the smallest. The input variables that have the largest new centroid in each of can type based on Minkowski distance are same with Euclidean distance successively are X_{3i}, X_{6i}, X_{4i}. The smallest new centroid of both the 1st and 2nd can types is X_{8i}, while of the 3rd can type is X_{8i}.

The new centroids in Table 2 - Table 4 are each used to calculate metric distances in (1) - (3) to re-classification cans by the type. The classification process based on each of the distance is carried out repeatedly until the members of each type of can do not move to other types of cans.

The results of this final classification for each metric distance are given in Table 5 - Table 7, while the level of accuracy of classification for each metric distance is given in Table 8.

Table 5. the final classification result using Manhattan distance

Manhattan distance		Grouping result into the can type		
		1	2	3
the can type	1	23	40	11
	2	15	53	15
	3	11	41	41

In Table 5, it can be seen that the classification results using Manhattan distance indicate that only in the 2nd can type, the number of cans that enter the can type should be (the 2nd cans type of can) is more than the other can types. In the 1st cans type, the majority of cans from the 1st cans type enter the 2nd cans type, while in the 3rd cans type, the number of cans that enter the 3rd can type is the same as the number of cans that enter the 2nd can type.

Table 6. the final classification result using Euclidean distance

Euclidean distance		Grouping result into the can type		
		1	2	3
the can type	1	34	35	5
	2	23	48	12
	3	12	45	36

The classification results using Euclidean distance as presented in Table 6 also show that only in the 2nd can type, the number of cans that enter the 2nd cans type of can is more than the other can types. In the 1st cans type, the number of cans that enter the 1st can type is almost the same as the number of cans that enter the 2nd can type, while in the 3rd cans type, the majority of cans from the 3rd cans type entered the 2nd cans type.

Table 7. the final classification result using Minkowski distance

Minkowski distance		Grouping result into the can type		
		1	2	3
the can type	1	31	37	6
	2	15	55	13
	3	13	44	36

The final classification using Minkowski distance in Table 7 shows that in the 1st can type, the number of cans from the 1st can type that enter the 2nd can type is more than the 1st cans type, as well in the 3rd can type, the number of cans from the 3rd can type that enter the 2nd can type is more than the 3rd can type. The accuracy level of classification using three different distances for combination the conveyor belt speeds and the lighting angles are given in Table 8 – Table 11.

Table 8. Accuracy level of classification using three different distances for angles of 30^0

No.	Metric Distances	Classification accuracy level (%)			
		Speed of 0.181 m/s		Speed of 0.086 m/s	
		Halogen	Incandescent	Halogen	Incandescent
1	Manhattan	20.8	27.2	36.0	39.2
2	Euclidean	24.4	40.0	42.8	42.0
3	Minkowski	25.6	40.0	38.0	38.4

Table 8 shows that the highest accuracy level of cans classification for speed of 0.181 m/s and halogen lamp is using Minkowski distance, while the both Euclidean and Minkowski distance has the accuracy level for incandescent lamp. For speed of 0.086 m/s, either halogen or incandescent lamp is using Euclidean distance.

Table 9. Accuracy level of classification using three different distances for angles of 45^0

No.	Metric Distances	Classification accuracy level (%)			
		Speed 0.181 m/s		Speed 0.086 m/s	
		Halogen	Incandescent	Halogen	Incandescent
1	Manhattan	35.8	30.4	46.4	29.6
2	Euclidean	49.6	34.0	42.8	28.0
3	Minkowski	40.8	35.6	42.8	27.6

The results in Table 9 notes that for speed of 0.086 m/s, either halogen or incandescent lamp, the highest accuracy level of cans classification is using Manhattan distance, while for speed of 0.181 m/s the highest accuracy is Euclidean distance for halogen lamp, and Minkowski distance for incandescent lamp.

Table 10. Accuracy level of classification using three different distances for angles of 60^0

No.	Metric Distances	Classification accuracy level (%)			
		Speed 0.181 m/s		Speed 0.086 m/s	
		Halogen	Incandescent	Halogen	Incandescent
1	Manhattan	37.6	28.8	29.6	29.2
2	Euclidean	34.0	24.4	28.0	28.0
3	Minkowski	35.6	32.4	29.2	28.0

Table 10 present that the highest accuracy level of cans classification for speed of 0.181 m/s is using Manhattan distance (halogen), and Minkowski distance (incandescent), while for speed of 0.086 m/s, either halogen or incandescent lamp is using Manhattan distance.

Table 11. Accuracy level of classification using three different distances for angles of 90^0

No.	Metric Distances	Classification accuracy level (%)			
		Speed 0.181 m/s		Speed 0.086 m/s	
		Halogen	Incandescent	Halogen	Incandescent
1	Manhattan	36.0	37.6	28.4	28.4
2	Euclidean	39.6	37.2	40.0	22.0
3	Minkowski	38.0	26.0	21.6	21.6

Table 11 shows that the accuracy level of cans classification using Euclidean distance has the highest accuracy for halogen lamp, and using Manhattan distance has the highest accuracy for incandescent lamp.

IV. CONCLUSIONS

This study developed a cans waste classification system based on RGB images capturing at two types of conveyor belt speed and four lighting angles. Implementation of three different metric distances on the k-means clustering method to classify the cans waste into three cans type indicates that the accuracy level of k-means clustering for three distance are not significantly different. The level of accuracy obtained is not satisfactory. The highest accuracy level of classification is obtained from data of captured image on the conveyor belt speeds of 0.181 m/sec, the lightings of halogen lamp, and the lighting angles of 45^0 by implementing the Euclidean distance at 49.6 %, while the lowest accuracy level of classification is obtained from data of captured image on the lighting angles of 30^0 with the same conveyor belt speeds and the lamp at 20.8 %.

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