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Development of a Data Clustering System for 2DOF Robotic Ball Balancer Using Laser Scanning RangeFinder

Gokhan BAYAR[1*]

Abstract

In this study, a new perspective for developing laser scanner rangefinder based data clustering system for a 2DOF robotic ball balancer was proposed. The study focused on detecting an object (i.e., ball) on the tilt-table robotic platform using the sensor fusion and data clustering systems proposed. Clustering system was modeled by following the principles of hierarchical clustering method. The developed system involving the clustering and sensor fusion algorithms was embedded in Matlab-Simulink environment to be able to run in real-time applications. The system was tested using an experimental platform including a 2DOF robotic ball balancer equipped with high resolution encoders and a laser scanner rangefinder. In the experiments, the goal was to detect the ball and its position not only on the flat but also on the tilted platform. A camera was also attached to the top of the experimental setup and used to monitor the location of the ball on the platform. By this way the results obtained using the proposed system could be verified for accuracy, performance and repeatability issues.

Keywords: Robotic ball balancer, laser scanner rangefinder, identification, object detection, sensor fusion, hierarchical clustering.

1. INTRODUCTION

Balancing systems are commonly used in automobile, space, aviation, maritime and manufacturing industries. They are utilized to adjust the systems which are under the effects of disturbances. The use of them gives ability to regulate the systems running in real-time operations. They are also used in the research & development applications of the robotic systems. In the control, automation, robotics, mechatronics, electronics and mechanical engineering education, such systems are placed in the education plans as well.

As well as using robotic balancers in research and industrial applications, they give opportunities to students to test the data mining and control algorithms and observe the results. For example,

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a robotic ball balancer system gives a chance to engineering students to adapt their theoretical knowledge to a real system and conduct some real experiments. Such systems whereby new methodologies like system dynamics, controller design, data clustering, object recognition, etc. can be tested.

Robotic balancers are designed to track desired reference inputs so the algorithms running inside the control block gain importance. In order to adapt control algorithms and mathematical expressions describing the motion of the system, accurate feedback information is needed and a robust data mining and sensor fusion system should be constructed to be able to handle this information.

In this study, a new characterization and data clustering system for a 2DOF robotic ball balancer integrated with a laser scanner rangefinder was proposed. The data clustering system was developed by using the principles of hierarchical clustering technique. It was used to obtain the ball position in two directions on the tilt-table. The system developed was tested using an experimental platform, which involved a 2DOF robotic ball balancer and a laser scanner rangefinder. 2DOF ball balancer was constructed using 2 sets of driving systems. Driving systems were built with gear couples and high resolution encoders. The use of encoders was able to give tilt angle information of the platform in two directions. The laser rangefinder sensor has ability to scan its surrounding in a range of 240^0. It can achieve a full scan with 0.36^0 angular resolutions in 0.1 s. The measurement capability of the laser scanner used in this study is between 60 mm and 4095 mm. As the computational and communication platform, Matlab-Simulink was used. In Matlab - Simulink, there is no available data clustering function that can be used in real-time operations. As one of the main contributions of this study, the clustering algorithm, developed based on the hierarchical clustering technique, was prepared using C/C++ programming language and embedded in Matlab-Simulink environment. The data coming from the high resolution encoders mounted on the balancing system were also acquired in the same computational system. In order to verify the accuracy and performance of the proposed system, a camera was attached to the top of the experimental platform.

This paper is organized as follows. In Section 2 relevant literature studies are reviewed. In Section 3 general information about clustering methods are presented. Hierarchical clustering is also explained in this section. In Section 4 the experimental setup constructed for this study is introduced in detail. In Section 5 experimental studies and their results are presented. The paper is concluded in Section 6 with an analysis of results.

2. LITERATURE STUDIES

Literature studies are given in the groups of balancing systems, laser scanner rangefinder based systems and clustering algorithms and their usage.

In [1], the balancing performance of an automatic ball balancer was taken into account. The study focused on investigating the performance of the system. Kinematic and dynamic modeling of the ball balancer was studied. In [2], analytical and experimental investigation of automatic balancing systems was studied. A dynamic balancer was designed and a monitoring system was created to observe the dynamics of the system. In [3], a laser scanner rangefinder based detection and tracking system was proposed. The system developed focused on tracking people. It also investigated the use of the system in mobile robotic and intelligent surveillance applications. The proposed system was constructed by using laser point clustering method to extract object locations. In [4], an agglomerative hierarchical clustering system was used to create a real-time plane extraction in point clouds. The sensor data was clustered to be able to detect the multiple planes. In [5], a laser scanner rangefinder was used together with a CCD color camera. To segment the flat areas and detect the planes, RANSAC search engine was adopted to the system. The use of proposed system gave ability to create a 3D space scene and merge the data coming from laser scanner and camera. In [6], a stepwise cluster technique was used to classify individual trees. The system used laser scanning rangefinder data as the data source. The unsupervised stepwise cluster algorithm was used to create groupings of similar objects at consecutive steps by adapting the k-medoid algorithm. In [7], laser scanner rangefinder was used to create an intelligent space algorithm. A position estimation methodology that was constructed based on the target shape information was proposed. To extract the target object, background subtraction and a basic clustering method were adapted to the system. In [8], Gaussian mixture model and robust structural matching were integrated to create a clustering system related to change detection in 3D environments. A hierarchical cluster system was built to create a binary tree based on splitting each region. The objective of this study was to adapt the proposed system for autonomous robotic applications. In [9], to achieve high speed rendering, hierarchical face cluster partitioning system was introduced. The study intended to reduce the computational time during rendering since a computer's rendering capability is generally not enough when the data load is high and high-quality rendering is expected. To solve such problems, a recursive clustering method was presented. In [10], a feedback system involving a laser scanner and monocular camera was presented. The objective was to create a data grouping system for improving robustness and precision in mobile robotic applications. In [11], a data clustering system for detecting, classifying and tracking of moving objects was proposed. The idea of the system was to use an octree model constructed using the principles of occupancy grid representation. The proposed method aimed to model the objects placed in the surroundings of the laser scanner. In [12], a data filtering system based on morphological methods was developed. The system was coupled with a laser scanner.

This paper addresses a laser scanner based clustering system for characterization of a tilt-table ball balancer. It looks for the solutions that use easy-to-use and easy-to-find computational platforms like Matlab-Simulink. The methodology introduced combines mathematical modeling, sensor data integration with the computational platform, sensor fusion, data decoding and clustering, and successful experiments with verification.

3. CLUSTERING METHODS

In data mining, many clustering methods have been developed. The reason of why there are many clustering methods is that each method has been created to achieve a special goal. Besides the goals, the mathematical backgrounds used to develop the clustering algorithms have also different principles. In [13], it is suggested that clustering methods can be specified into two groups; hierarchical and partitioning methods. The study [14] offers to categorize the clustering methods into three groups; density based, model based clustering and grid based methods. The details about the groups of clustering methods can be seen in [14, 15].

3.1. Hierarchical clustering

Hierarchical clustering is a commonly used data analysis approach in data mining applications. The main principle of this approach is that the method searches for creating linkages between data based on hierarchy of the data clusters. There are two groups of hierarchical clustering; agglomerative and divisive techniques. The first technique seeks to build a clustering system in which each object initially represents a cluster of its own. Once the clustering algorithm is initiated, the clusters built are connected until the ultimate data grouping operations is achieved. The latter technique offers an approach proposing that all the objects are located in a unique cluster. Then the cluster is divided into sub groups. This process continuous until the desired data grouping is achieved. To build desired clusters, operations of merging or dividing clusters should be performed by following some optimization constraints. There are three commonly used operations. They do similarity measurements called single-link, complete-link and average-link clustering methods. Single-link clustering is the nearest neighborhood method. It searches the distance between two clusters or one cluster and one member or two members. The method looks for the minimum distance to build similarity groups

[15, 16]. The similarity criteria are defined according to the types of objective. Complete-link clustering is known as furthest neighborhood method. It tries to find the maximum distance between two clusters or one member and a cluster [15]. Same as with single-link clustering, searching criteria are defined to meet the aim of the data clustering. Average-link clustering technique uses the principles of minimum variance approach. The method considers the average distance between two clusters or one member and one cluster or one cluster and any member of other clusters [15].

In this study, single-link hierarchical clustering algorithm is adapted to the experimental system. As mentioned above, this technique is known as the minimum distance clustering or nearest neighborhood clustering. In real-time data mining applications, this method is commonly preferred since a standard personal computer would be enough to construct and run it. It does not require using of high capacity of RAM, number of processors, high volume storage for hard-disc, etc. The main idea of the single-link hierarchical clustering is represented in Figure 1-a. The minimum distance between two clusters specified by (d) should be obtained using the algorithm constructed. This process should continue until the last member of the data set is included in a cluster.

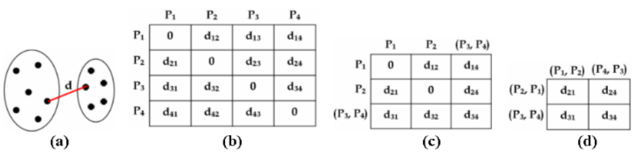


Figure 1. (a) Main idea of the clustering, (b, c, d) Distance matrices of the clusters.

The methodology of the single-link hierarchical clustering technique adapted to this study is explained by using a simple data set. Suppose that we have 4 members (P_1, P_2, P_3, P_4) in the data set. In the first step, the distances between each point are calculated (d_{12}, d_{13}, d14, d_{23}, d_{24}, d_{34}). Then, a 4 by 4 input distance matrix is created as shown in Figure 1-b. Now we have a big cluster.

In the second step, the smallest value should be found. Assume that the minimum distance information is d_{43}. In this case, two members should be merged. This merge operation is shown in Figure 1-c. In the next step, one more merging operation should be performed. Assuming the smallest value is d_{12}. The merge operation is resulted as shown in Figure 1-d. In the last step, the minimum distance can easily be found and clustering is completed. By using the information obtained above, a tree diagram can be drawn as shown in Figure 2-a. The clustering hierarchy can also be plotted as given in Figure 2-b.

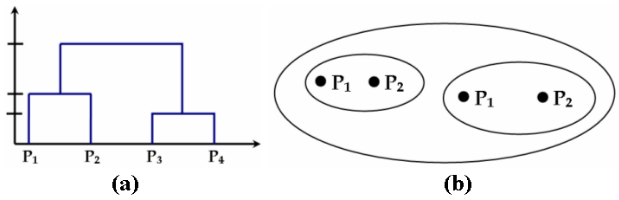
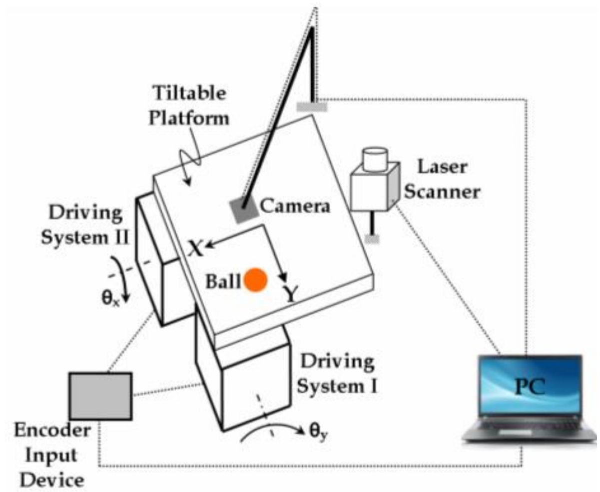
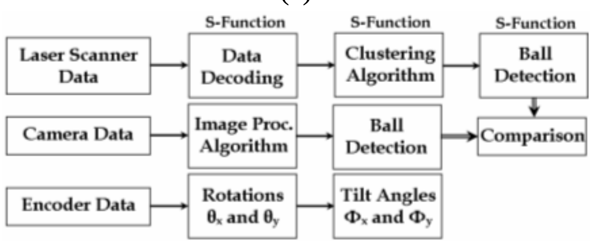


Figure 2. (a) Data tree showing data clustering steps, (b) Clustering hierarchy.

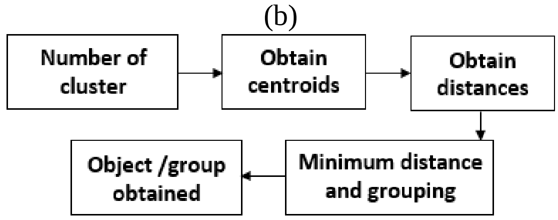
4. EXPERIMENTAL SETUP



(a)



(b)



(c)

Figure 3. (a) Experimental set-up, (b) Block diagram of the proposed system, (c) Flow chart of the clustering algorithm.

In this study, an experimental setup shown in Figure 3-a was constructed. It involves a robotic balancer, a laser scanner rangefinder and a camera attached to the top of the platform. Robotic balancer includes two driving systems manufactured by Quanser Company (SRV02) and high resolution quadrature encoders mounted to the driving units. The angular resolution of the encoders is 4096 pulses per revolution. In order to communicate with the encoders and count their pulses, an encoder input card, manufactured by Quanser Company (Q2-USB), was also added to the system. The platform (table) can be tilted in two (X, Y) directions (Figure 3-a). The block diagram used for data processing tasks is illustrated in Figure 3-b. Flow diagram of the clustering algorithm developed is demonstrated in Figure 3-c as well. The tilt angles are obtained using the kinematics of the system and information coming from the encoders (mounted at point O – Figure 4). The kinematic model of the driving units and the tilted platform is shown in Figure 4. In this schematic, the link lengths are specified by L_1, L_2, L_3 and the radius of driving unit is shown by R. Angular rotation and tilt angle are specified by θ and Φ, respectively. This schematic is given to represent one DOF of the balancing system. The other DOF system is identical, so the second tilt angle can also be obtained using the rotation information from the second high resolution encoder.

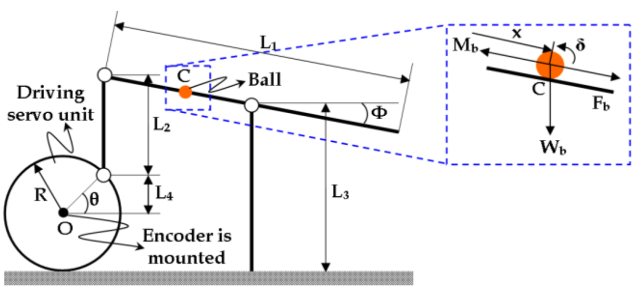


Figure 4. Geometric model of the balancing system.

Considering the balancing system (Figure 4) and the ball (highlighted by the dashed-line-rectangle in Figure 4), equation of motion of the system can be built in the following order (Equations 1 through 6) [17]. This modeling strategy is used for the control, sensor fusion and data mining purposes.

$$m_{ball}a_{ball} = F_{sum} = F_I + F_G \tag{1}$$

where forces caused from the inertia of the ball and gravitational acceleration are indicated by F_I and F_G, respectively. Mass and acceleration of the ball are specified by m_{ball} and a_{ball}, respectively. The forces caused by gravity in x and y directions can be written as:

$$F_G = m_{ball}\, g \sin(\Phi) \tag{2}$$

The force created by the ball rotation is constructed as:

$$F_I = \frac{J_{ball}\,x}{r^2_{ball}} \tag{3}$$

where r_{ball} indicates the radius of ball used in this study. Combining the equations above yields the following relationship:

$$\ddot{x} = \frac{m_{ball}\, g \sin(\Phi) r^2_{ball}}{m_{ball} r^2_{ball} + J_{ball}} \tag{4}$$

From the geometry given in Figure 4, one can find:

$$\sin(\Phi) = \frac{2R\sin(\theta)}{L_1} \tag{5}$$

Inserting Equation (5) into Equation (4) gives the following equation of motion for the ball:

$$\ddot{x} = \frac{2\theta m_{ball} g R r^2_{ball}}{L_1\left(m_{ball} r^2_{ball} + J_{ball}\right)} \tag{6}$$

To feed the developed data clustering system and obtain the ball position on the platform, a laser scanner rangefinder sensor (Hokuyo URG-04LX - Figure 5-a) was attached to the balancing system. The baud rate speed of the laser scanner can be set to 19.2, 57.6, 115.2 and 500 Kbps. In this study, the speed was adjusted to 19.2 Kbps and the communication was achieved through

RS232 serial protocol. The angular resolution of the laser scanner is about 0.36^0 (360^0 / 1024) and the scanner is able to scan its surroundings from 0^0 to 240^0 (Figure 5-b) in 0.1 s. The minimum and maximum measurement distances, and the resolution are 60 mm, 4095 mm and 1 mm, respectively. The mounting tool designed to locate the laser scanner range finder in the experimental system is also illustrated in Figure 5-c.

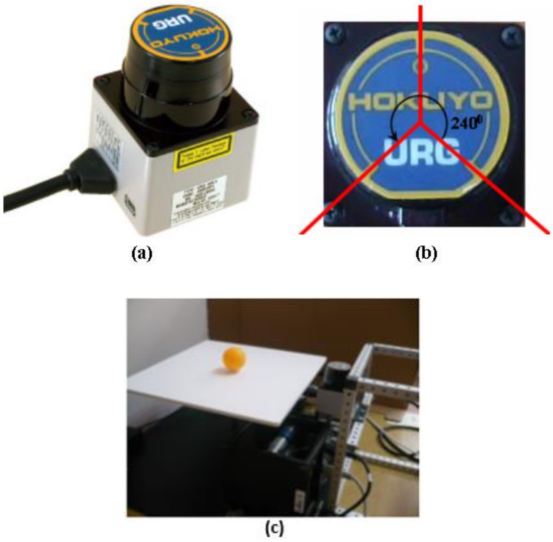


Figure 5. (a) Hokuyo URG-04LX laser scanner rangefinder, (b) Scanning range, (c) Installing laser scanner rangefinder sensor to the system.

The real-time Workshop toolbox of Matlab-Simulink was used for all experimental studies. The block diagram of the system is presented in Figure 3-b. The encoder input card, laser rangefinder and camera were run together inside Simulink block. The data coming from the laser scanner rangefinder was decoded by the use of S-function feature of Matlab (Figure 3-b) for real-time use. The laser scanner sends a packet containing 1435 bytes with 683 equal intervals. The data package content is shown in Figure 6-a. Each distance value having length of 12 bytes is represented with two parts specified by D_A and D_B. An example for decoding process of the sensor data is shown in Figure 6-b. The placement of the laser scanner in the experimental area is illustrated in Figure 7-a. Using the distance (shown by d) between the laser scanner and the platform, the angle δ is obtained. By this way data clustering is performed from the angle δ to the angle (1800 - δ). This reduces the data size and processing time.

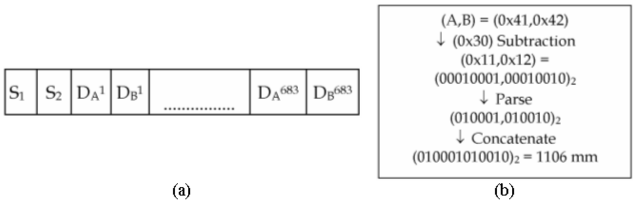


Figure 6. (a) Data packet sent by the laser scanner, (b) Data decoding process.

The other unit of the experimental platform is the camera located at the top (Figure 3-a). It was exactly placed at the point which was coincident with the geometric center of the tilt-table. The camera was used to detect the ball and find its location on the platform so that the results obtained using the developed clustering system could be verified.

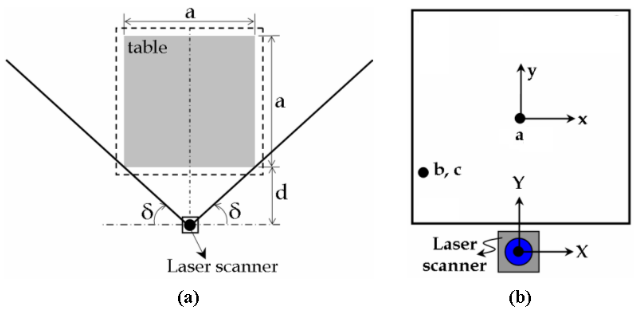


Figure 7. (a) The placement of the laser rangefinder sensor. (b) 3 different test cases. Each letter indicates a different ball position on the platform. The cases specified by a and b are tested on the flat platform whereas the experiments of the case shown by c are performed on the tilted platform.

5. EXPERIMENTAL STUDIES

The clustering algorithm developed was tested using the experimental set-up introduced above. The objective of using the experimental set-up was to detect the ball position on the platform for different cases. The geometric representation of the platform and the test locations are shown in Figure 7-b. The placement of the laser scanner rangefinder is also illustrated in this figure. Two coordinate axes, (x, y) and (X, Y), were located at the geometric center of the platform and the laser scanner's mounting point, respectively. Different test cases were considered. Each case was thought to create a different characteristic so that the behavior of the proposed system could be evaluated. The test cases are specified by the letters of a, b and c (Figure 7-b). As well as conducting experiments on the flat positioned table (cases a and b), the ball positions were detected on the table which was tilted (case c). The experiment results were verified by using the camera + image processing algorithm.

The data coming from the laser scanner and the clustering results for the case (a) are presented in Figure 8. In this case study, number of clusters are created and specified by different colored points. The cluster indicating the ball position on the table is highlighted with the red points inside the dashed square shape. The detected ball center is also shown via the asterisk (*). In order to provide a clear presentation, the data of the ball cluster is given in a zoomed view. The results indicate that the ball is placed at -15 mm and 174 mm in X and Y directions, respectively. Note that this test was performed on the flat positioned table (i.e., $\Phi_x = 0^0$ and $\Phi_y = 0^0$).

Three different test cases are presented in Figure 9. In Figure 9-a, the ball is placed at the geometric center of the platform (case a). The tilt angles in X and Y directions are zero. In the right image of Figure 9-a, the results obtained using the clustering system is presented. The image processing results are also shown in this figure. The location of the laser scanner is specified with the black colored square. The detected ball position is also given in a zoomed view. The clustered laser and camera data are specified with red and green points, respectively. The ball center obtained is highlighted via black-diamond (laser data) and blue-square (camera data) filled shapes. The position values in X-direction are found as $X_b = 166.24$ and ${}^{C}X_b = 163.80$ mm by the use of (laser scanner + clustering system) and (camera + image processing), respectively. In Y-direction, the position values are detected as $Y_b = -3.02$ and ${}^{C}Y_b = 0.33$ mm, respectively. Note that the laser scanner was located at (0, 0) position showing the center of the coordinate axes.

In the second case study (case b), the platform is still flat however the ball is moved from the center. The results are presented in Figure 9-b. The data showing the ball and its center are also exhibited in a zoomed view. In this test, the ball center is detected as -116.49 mm (laser scanner + clustering system) and -114.74 mm (camera + image processing) in X-direction, and 123.96 mm (laser scanner + clustering system) and 125.34 mm (camera + image processing) in Y-direction. In the third case (case c), the ball position is nearly same as with the case given in Figure 9-b, however the platform is tilted in both X and Y directions about 29^0 (Figure 9-c). The clustering system gives the ball center position as (-118.61, 125.74). These values are found as (-118.93, 133.56) by the use of camera. To show the variations in the ball position results obtained, Table 1 is prepared for the cases (a), (b) and (c). As seen in this table, minimum, maximum, mean and standard deviation values are given. (The speed of the data flow is determined by the slowest unit of the experimental system, which is the laser scanning range finder. It works with 10 Hz running frequency, which has the meaning of that 10 samples are taken from the sensors in each second. In the experiments, the data is taken for more than one second and the clustering algorithm is run for this time instances. By this way, minimum, maximum and mean values are obtained. Standard deviation values are also obtained in order to show the measure of the amount of variation of the data collected and analyzed in this time interval). Locational outputs in Case (a) are obtained in the range of 166.61 mm to 168.44 mm in X-direction. The average value of the experiments (in X-direction for Case (a)) is 166. 24 mm. The camera output gives the location information as 163.80 mm. This means that the location in X-direction is obtained with 1.49% estimation error. Clustering system yields nearly 6% estimation error in Y-direction for Case (a). Errors in X-direction are obtained as rougly 1% and 0.2% for Case (b) and (c), respectively. Those values are calculated as 1.1% and 5.8% in Y-direction.

Table 1.
Ball position results obtained for the Case (a), (b) and (c) specified in Figure 7-b. Flat platform positioning are the cases of (a) and (b). Case (c) specifies the tilted platform.

		Camera	Min	Max	Mean	Std
Case (a)	X_b	163.80	166.61	168.44	166.24	0.99
	Y_b	0.33	-3.21	2.58	-0.31	0.07
Case (b)	X_b	-114.74	-117.70	-115.35	-116.49	0.62
	Y_b	125.34	122.50	125.75	123.96	0.74
Case (c)	X_b	-118.93	-119.83	-117.56	-118.61	0.62
	Y_b	133.56	124.65	127.03	125.74	0.63

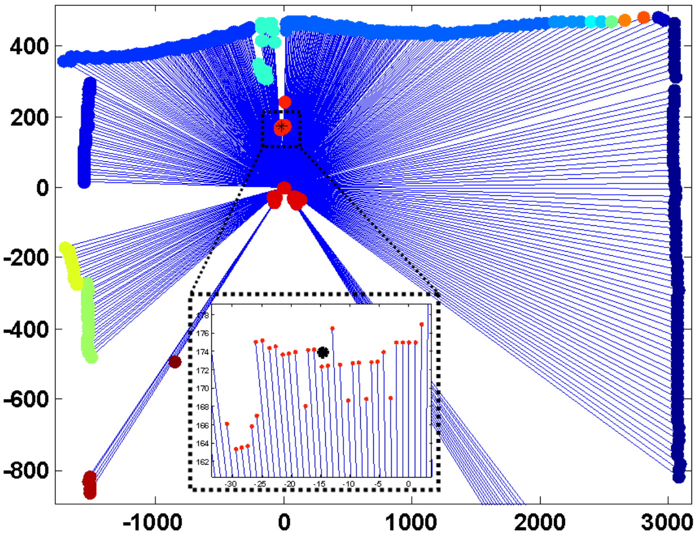


Figure 8. Scanned data of the laser scanner for the case (a). The colored points show the data clusters obtained using the proposed clustering system. The ball center is also specified by the asterisk (*). Dimensions are in mm.

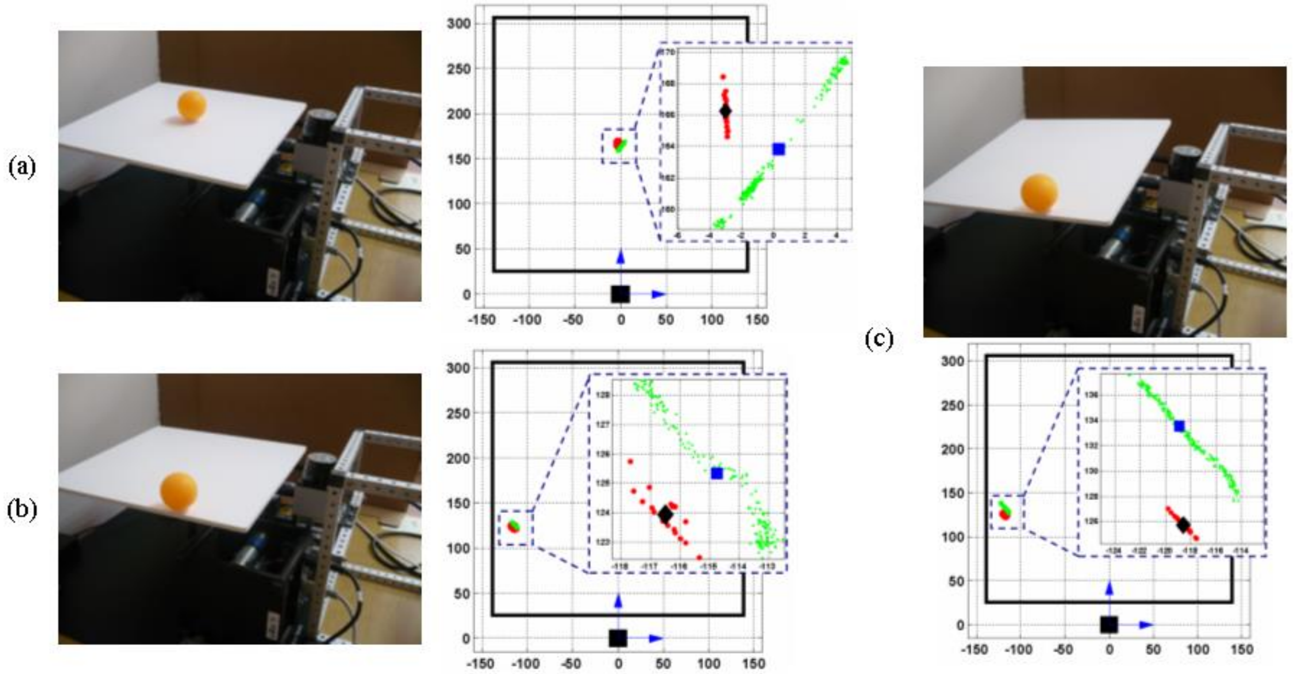


Figure 9. Data clustering experiments for the cases a, b and c. Laser scanner position is represented via black-colored square. The results obtained by using the proposed clustering system (X_b, Y_b) and camera (^cX_b, ^cY_b) are shown by red and green points. Black-diamond and blue-square shapes specify the ball center positions detected.

6. ANALYSIS AND CONCLUSION

Balancing systems are commonly used for the research and educational purposes. New approaches focused on developing models and control systems for balancing platforms are also continuously carried out by the scientists and research engineers. In this study, a new data clustering procedure for a 2DOF ball balancing system, designed for small-scale research activities and educational purposes, was taken into account. The ball balancer has a configuration that it can be tilted in two rotational directions. A laser rangefinder sensor was integrated with this system. To get the tilt information of the platform, two high resolution encoders were mounted on the system. To verify the results obtained using the proposed system, a camera was attached to the top the platform. The clustering system based on the hierarchical clustering technique was developed in order to detect the ball and its position on the platform. The whole system was implemented in Matlab-Simulink for real-time use. The clustering system was tested in the flat and tilted positions of the platform. Different scenarios were tested to see the performance, accuracy and repeatability of the system introduced. The results indicate that the proposed system involving the sensor fusion and data clustering algorithms would be used for further research activities like mathematical modeling, robust and intelligent control of the robotic balancing platforms. The system including clustering algorithm and a laser scanning range finder can be integrated into any balancing platform on which the object should be detected. It can be able to detect the object’s location without interesting the lighting conditions of the working environment. This provides an advantage over using camera based solutions. It also gives opportunities than using ultrasonic sensor based, radar & sonar based and mechanical & digital switches based solutions. The algorithm proposed does not also require high capacity of processing equipment like ram, hard disk, processing unit, DAQ card, etc. Professional experience about installing and using mechatronic systems is not needed as well to be able use the system proposed in this paper.

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The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the author.

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The author declares that this document does not require any ethics committee approval or any special permission.

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