Parcel Transportation System with 3D Image Analysis

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Abstract

Carpooling is an interesting alternative to the classic "hub and spoke" model that may make freight distribution more sustainable. Our idea combines Artificial Intelligence and mobile technologies to optimally exploit the untapped transportation capacity that commuters have at their disposal to deliver goods. However, since the transport is not entrusted to professionals, we need to track the parcel throughout the network in order to avoid any loss or damage. Images of the parcel are taken at various stages to record its condition and automatically detect damage. In this paper, we discuss a solution based on histogram of normalized vectors to detect any deformation on a parcel using 3D image analysis of the object.

Keywords

package, deformation, 3D-comparison, carpooling, mesh

1. Introduction

Today, most parcel distribution systems are based on the "Hub and spoke" model. This model requires that all the parcels in the system pass through one of the few central hubs before being delivered (in all of Switzerland there are only four hubs). The high automation and the possibility to process large number of parcels makes these centers very efficient. However, this approach presents three unsolved issues: first, having to go through one of the hubs, the path of the parcel is not the shortest possible and therefore it is not the one with a lower environmental impact; second, in the final link of the delivery chain (i.e. "last mile delivery") the optimization breaks due to the multiplicity of destinations to serve, constituting up to 28 % of the total delivery cost [1]; third, the hubs represent single points of failure, meaning that a problem on one of them may have dramatic consequences for all the network.

This complexity will keep on growing due to the continuous increase in online sales, additionally boosted by the COVID-19 pandemic.

To tackle these challenges and enable sustainable smart cities, we have proposed BombusCar [2], an intelligent platform that combines Artificial Intelligence (AI), mobile technologies,

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gamification and computer vision to create a smart, dynamic, engaging and secure crowd-based solution for parcel delivery. In this paper, we focus on only one aspect i.e. deformation detection of parcels in order to guarantee the safe and secure delivery of the parcel. As the proposed package delivery is based on carpooling, the packet is exchanged between multiple, non-professional parties. This may result in an external damage to the consignment somewhere in the distribution chain difficult to detect. Therefore, it is important to record the condition of the package at various stages so that, in case of a problem, it can be tracked back. In particular, we have suggested to record the package in 3D every time the parcel is exchanged between two entities, apply segmentation techniques and detect deformation, if any, in an automatic way using image processing. For the scope of this project, we limit the packing material to a cardboard as it is the most common and durable packaging material.

Previously, measuring the deformation on a cardboard box or a surface has been studied in literature using classical methods. Techniques that use big arrangements like X-ray tomography [3] and industrial optical system in 3D [4] to measure the deformation are not suitable for applications that require a small scale setup. In [5], the author measures the deformation on a wall using the depth in a static setup. This approach, when applied on a box, would require registration of each side individually. The study done in [6] addresses this issue by comparing 3D objects using a geometrical approach in 2 steps: a) pose estimation, b) similarity measurement. The approach proposed in this paper aims to eliminate the requirement of pose estimation or object registration before comparison, which makes it simpler to use in application like ours where the object is handled by different people in different locations implying variable external conditions.

The paper is organized as follows. In Section 2, we provide an overview of the package transportation system along with different stages at which the package is exchanged and images are taken. Section 3 talks about the acquisition of a 3D model of the packages and explains our approach to detect any deformation. Finally, in Section 4, we discuss the results.

2. The BombusCar Distribution System

BombusCar's network is composed of 4 types of actor: the *Sender* - the person or the retail company sending the parcel; the *Carrier* - the person transporting the parcel; the *Collector* - the person storing the parcel temporarily (this role allows the connection between different Carriers and, therefore, to achieve a wider, more flexible and more capillary distribution); the *Recipient* - the person receiving the parcel.

An optimization algorithm based on genetic algorithms [7] considers the needs and capabilities of all the actors and parcels present in the network and it proposes, for each parcel, a list of *appointments*. An appointment simply describes the time, the place and the two actors involved in one exchange. If all the actors taking part in the distribution chain of a given parcel, from the sender to the recipient, accept their appointments, the delivery can start.

The exchange is composed of two simple steps. In the first step, the actors identify with each other using a unique, automatically generated QR code. The incoming actor shows the QR code on the smartphone screen and the actor currently holding the parcel scans the QR code. The application notifies if the match is successful and, if that is the case, the exchange can proceed. In the second step, the new parcel holder uses the scanning system integrated in the mobile app to take a picture of the parcel. The system automatically records the new entry and provides a measurement of the deformation on the parcel by comparing the new data with the previously acquired ones. Obviously, this comparison is not possible at the very first exchange (e.g., between the Sender and the first Carrier). In this case, the first picture is only needed as a reference for the following exchanges.

The same approach is repeated at each exchange until the parcel is delivered to the Recipient. In case of a problem, the mobile application allows notifying all the involved users and, if necessary, the package could be sent back to its starting point. In this paper, we focus on this second step and, in particular, on the approach that we propose to automatically detect deformations on the package.

3. Methodology

3.1. 3D Data Acquisition System

Acquisition of a 3D object is a challenging task. The most common approach includes using multiple 2D images such as multiview stereo imaging [8, 9] to apply 3D reconstruction. Currently, deep neural networks are also being used for the 3D reconstruction of scenes [10, 11]. Recent works have shown that 3D reconstruction is possible with mobile phones as well [12, 13].

In this paper, the focus is not on the 3D reconstruction but its application to find deformation by comparing different 3D objects. Therefore, we created a 3D model of the package by using a 3D scanner i.e. Calibry scanner [14] and the Calibry Nest software [15] for post-processing. As we scan parcels made of card boards which are symmetrical and have the same color (no distinct features present), we need to add some external markers placed close to the object (Fig. 1) before scanning.

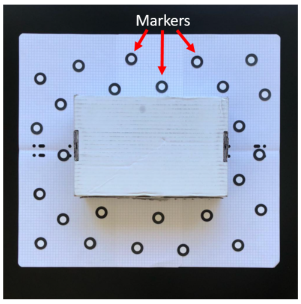
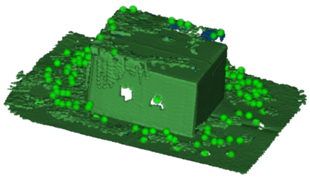


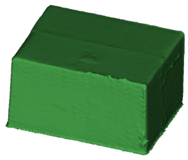
Figure 1: Setup for scanning a box with the nearby markers used for 3d reconstruction.

The scanner is revolved around the object such that it takes images of the object from all views. The scanning process takes around 60 to 90 seconds. It is worth noting that the object is placed on top of a table and the bottom side of the object will not be visible (i.e., the box will have only five sides).

Once the object is scanned, the misalignment and unwanted points are removed in post-processing. This involves discarding the bottom surface as these points do not belong to the



(a) Mesh of the scanned box. The markers are shown as green circles.



(b) Final mesh of the box after filtering small surfaces and fixing holes.

Figure 2: This figure illustrate the process of mesh cleaning, before the cleaning (a) and after the processing (b).

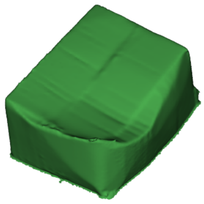


Figure 3: The end result of mesh cleaning on the deformed box.

object but to the table on which the object is placed. Fig. 2 shows the box before and after applying post-processing. The resulting mesh object shown in Fig. 2b is saved to be compared with the crushed box.

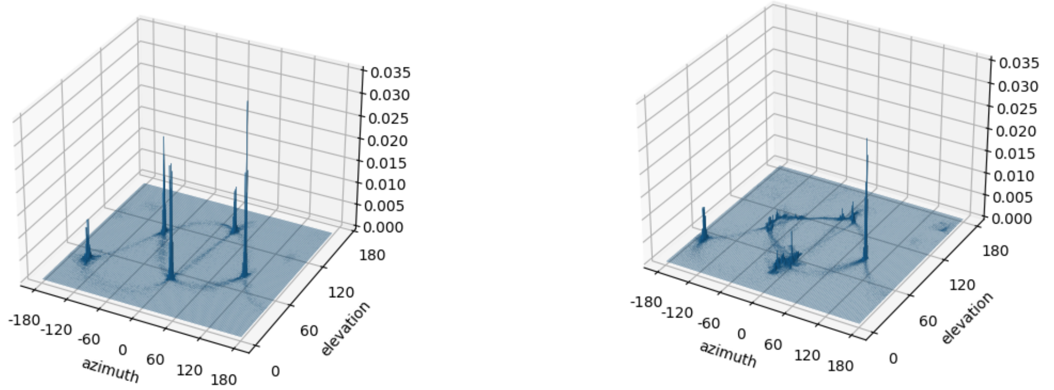
A deformed box is scanned in a similar procedure. The final mesh is shown in Fig. 3.

3.2. 3D Object Comparison

We compare the mesh of a deformed box against the original box which has not been damaged by analysing the histogram of normal vectors on the box. We exploit the fact that a non deformed box, placed on a flat surface, will have five rectangular segmented planes while a damaged box will not be properly segmented.

The first step is to compute normal vectors of the object. Ideally, the scanned box should have normal vectors in five directions, one direction for each plane. Practically, the normal vectors close to the edges of the box are not oriented in the same direction. The normal vectors are transformed into spherical coordinates from Cartesian coordinate system so that it is easier to visualize them. In spherical coordinates, only azimuth and elevation angles are required to represent them as their length is 1. Hence, they can be shown easily in 2D.

An intact rigid box has five segregated peaks (see Fig. 5). For a deformed box, the number of sharp peaks are reduced and a few small peaks appear. Obtaining the top five peak values gives the direction of normal vectors on each side of the plane. These values are used to divide the points on the mesh into different planes. An offset of 20 degrees in elevation angle while 40 degrees in azimuth has been used for segmentation.



(a) Rigid box.

(b) Deformed box

Figure 4: Normalized histograms of a rigid, not deformed box (a) and of a deformed box (b).

(a) Rigid box.

(b) Deformed box.

Figure 5: Segmentation box - Bottom view. Black points do not belong to any segment.

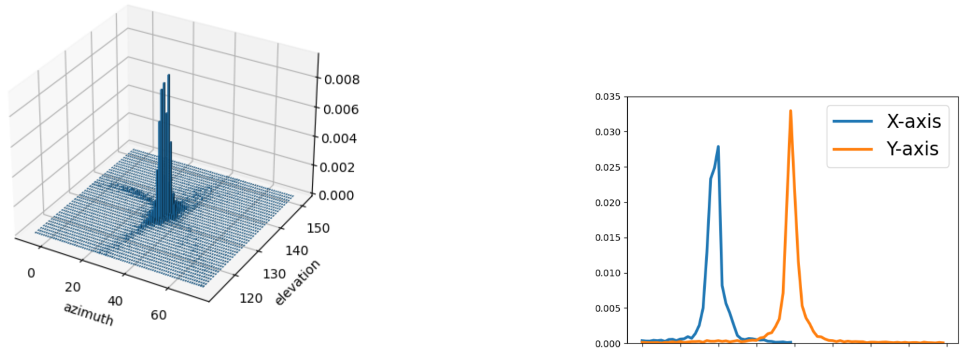
In order to detect deformation in a box, the following parameters have been used:

1. *Non-Associated points*: after the segmentation process, there are still some points that do not belong to any of the planes (shown in black color in figure 5). These points are called non-associated points. The ratio of these points is directly proportion to the damage on the box. In a good box, this ratio will still not be zero because of the edges on the box.
2. *Kurtosis*: also known as the fourth moment of a distribution, kurtosis describes the difference between a given distribution and a normal distribution.

The peaks extracted for segmentation are analyzed individually. Each peak is projected on X and Y axis by adding all the points. Then, on this projected X and Y plots, the fourth moment, i.e., kurtosis is computed. This is done for the top five peaks in each case.

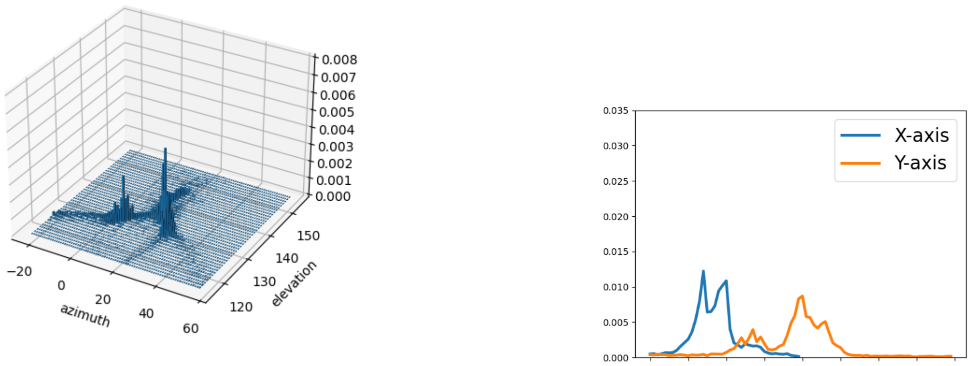
In our case, for a good box, the five peaks in a histogram should be higher and have a positive Kurtosis value. Whereas, for a damaged box, this value should be relatively lower.

Hence, based on the Kurtosis value and non-associated points in a segmented 3D mesh, we detect the deformation in a box. The biggest advantage of this method is that it does not require the objects to be in the same pose, which is a limitation when dealing with 3D objects normally.



(a) Extracted Peak. (b) Projection on X (azimuth) and Y (elevation) axis.

Figure 6: Example of individual peak to apply statistical measurement on a rigid box.



(a) Extracted Peak. (b) Projection on X (azimuth) and Y (elevation) axis.

Figure 7: Example of individual peak to apply statistical measurement on a deformed box.

4. Results and Discussion

We use two brown colored single wall card board boxes of dimension 25x18x12 cm^3 and 23x19x12 cm^3.

(a) Original box. (b) Deformed box.

Figure 8: Box 1 in its original shape (a) and after that was deformed (b).

(a) Original box (b) Deformed box.

Figure 9: Box 2 in its original shape (a) and after that was deformed (b).

Both boxes are first scanned in good condition. Then the boxes are deformed by applying force on the top face for one box, and side face on the other box (see Figures 8 and 9). The boxes are scanned again in this condition.

Based on the above-mentioned boxes, Tab. 1 shows the increase in non-associated points of a deformed segmented box.

Table 1
Non-Associated points in segmented box.

	Non-Associated points %
Box 1 original	5.6
Box 1 deformed	12.0
Box 2 original	6.1
Box 3 deformed	29.7

The results are based on the complete histogram. Now, we take the top five peaks individually to measure kurtosis. We choose a threshold value of 5 on either X or Y axis, meaning that if one of the value is less than 5, the side is deformed.

Table 2
Kurtosis of the five peaks projected on X and Y axis.

Peaks	**Box1**				**Box2**			
	Original		**Deformed**		**Original**		**Deformed**	
	X	**Y**	**X**	**Y**	**X**	**Y**	**X**	**Y**
1st	12.7	19.6	9.9	15.9	10.4	20.8	6.5	7.0
2nd	21.8	21.0	**2.7**	**4.4**	14.3	15.8	7.9	13.3
3rd	13.8	18.8	8.9	18.2	13.4	21.6	**2.8**	**3.0**
4th	9.8	14.0	**4.2**	**4.7**	7.1	11.5	**1.9**	**2.8**
5th	8.0	12.0	**1.7**	**3.1**	5.7	8.0	**3.2**	**2.8**

In the Table 2, it can be seen that three sides of boxes have been damaged in the deformed version of the box. For box 1, 2nd, 4th and 5th sides whereas for box 2, it is 3rd, 4th and 5th side.

All these values are under the threshold of 5.

5. Conclusion

We present a 3D image analysis to identify package deformation in context of an intelligent and secure package transportation system for the smart cities of the future. The complete system is composed of different actors that exchange parcels based on the suggestions of a genetic optimization algorithm. During the distribution chain, to ensure the safety of the package, this paper proposes a method to automatically detect external deformations on 3D models. The deformation is detected via normal vectors on the surface of the box and statistical analysis of its histogram. This method removes the need of pose estimation before comparing 3D objects.

The current study is limited to a single use case (i.e., card board box) and was tested on a small dataset. In the future, we aim to extend our research to different materials and shapes. Our goal is to streamline the process and create a standalone mobile application capable of applying 3D reconstruction directly on the images taken with a consumer smartphone and able to detect possible deformations.

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References

[1] L. Ranieri, S. Digiesi, B. Silvestri, M. Roccotelli, A review of last mile logistics innovations in an externalities cost reduction vision, Sustainability 10 (2018) 782.

[2] F. Carrino, Q. Vaucher, R. Pasquier, V. Bourquin, O. Abou Khaled, E. Mugellini, S. Gobron, Bombuscar : gamification design of a carpolling-based freight transport, Proceedings of GSGS'20 : 5th Gamification &; Serious Game Symposium, September-November 2020, Switzerland (2020) pp. 79–82. URL: http://hesso.tind.io/record/6842, online Edition.

[3] D. Eriksson, C. Korin, F. Thuvander, Damage to carton board packages subjected to concentrated loads, 2014.

[4] P. Böröcz, Measurement and analysis of deformation shapes on corrugated cardboard logistical boxes under static and dynamic compression, 2015.

[5] T. Teo, 3d deformation measurement of concrete wall using close-range photogrammetry, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives 43 (2020) 1175–1179.

[6] M. Novotni, R. Klein, A geometric approach to 3d object comparison, in: Proceedings International Conference on Shape Modeling and Applications, IEEE, 2001, pp. 167–175.

[7] D. Whitley, A genetic algorithm tutorial, Statistics and computing 4 (1994) 65–85.

[8] Y. Hou, J. Kannala, A. Solin, Multi-view stereo by temporal nonparametric fusion, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 2651–2660.
[9] J. L. Schönberger, E. Zheng, J.-M. Frahm, M. Pollefeys, Pixelwise view selection for unstructured multi-view stereo, in: European Conference on Computer Vision, Springer, 2016, pp. 501–518.
[10] Y. Yao, Z. Luo, S. Li, T. Fang, L. Quan, Mvsnet: Depth inference for unstructured multi-view stereo, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 767–783.
[11] Z. Murez, T. van As, J. Bartolozzi, A. Sinha, V. Badrinarayanan, A. Rabinovich, Atlas: End-to-end 3d scene reconstruction from posed images, arXiv preprint arXiv:2003.10432 (2020).
[12] O. Muratov, Y. Slynko, V. Chernov, M. Lyubimtseva, A. Shamsuarov, V. Bucha, 3dcapture: 3d reconstruction for a smartphone, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2016, pp. 75–82.
[13] S. Chen, Z. Song, F. Gu, Z. Song, 3d reconstruction based on smartphone and extra light source, in: 2018 IEEE International Conference on Real-time Computing and Robotics (RCAR), IEEE, 2018, pp. 196–200.
[14] Thor3D, Calibri scanner, 2021. URL: https://thor3dscanner.com/en/products/calibry/, accessed: 2021-11-30.
[15] Thor3D, Calibri Nest software, 2021. URL: https://thor3dscanner.com/en/software/calibry-nest/, accessed: 2021-11-30.