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Enhancing Airplane Boarding Procedure using Vision Based Passenger Classification

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***Abstract*— This paper presents the implementation of a new boarding strategy that exploits passenger and hand-luggage detection and classification to reduce the boarding time onto an airplane. A vision system has the main purpose of providing passengers data, in terms of agility coefficient and hand-luggage size to a seat assignment algorithm. The software is able to dynamically generate the passenger seat that reduces the overall boarding time while taking into account the current airplane boarding state. The motivation behind this work is to speed up of the passenger boarding using the proposed *online* procedure of seat assignment based on passenger and luggage classification. This method results in an enhancement of the boarding phase, in terms of both time and passenger experience. The main goal of this work is to demonstrate the usability of the proposed system in real conditions proving its performances in terms of reliability. Using a simple hardware and software setup, we performed several experiments recreating a gate entrance mock up and comparing the measurements with ground truth data to assess the reliability of the system.**

***Index Terms*— computer vision, agility measurement, boarding strategy**

I. INTRODUCTION

A common issue in airline industry is the minimization of the time airplanes spend on the ground at the airports. This time, which is usually referred to as turnaround time (TAT), requires therefore special attention. Among the different ground operations that are performed during the TAT, passengers boarding cannot be easily parallelized since it cannot start until other processes, such as fueling, cleaning and catering, have been successfully completed. Hence, the boarding process plays an important role with respect to the TAT since it is on its critical path [1]. The main objective of this paper is to present the implementation of a new boarding strategy that is able to reduce the overall boarding time by exploiting an *online* seat assignment algorithm based on passenger and hand-luggage classification. In order to provide the opportune data to the boarding software, the proposed system makes use of vision sensors and image processing algorithms.

In the past few years computer vision systems (CVS) have been widely employed to enhance the performances of transportation systems and the infrastructures related to them. The main objective of such usage has to be found in the fact that by making transportation systems sensing the human environment around them, they can actually respond according to the environment changes. The field of autonomous driving, for instance, constitutes one of the most common field of application: intelligent vehicles make use of vision based pedestrians and vehicles detection for fast decision making and collision avoidance or traffic analysis and monitoring.

In the previous literature, works that have considered the application of CVS in airports mainly focus on the employment of cameras for surveillance [2] or boarding control [3]. In our previous work [4] a different application of computer vision dealing with the speeding up of passenger boarding into airplanes has been proposed. In this work a seat allocation algorithm exploiting passenger and luggage data is compared to currently used boarding strategies and it shows better performances in terms of saved time in the overall boarding phase.

In this paper we propose the validation of the optimal boarding strategy proposed in our previous work, where it has been demonstrated that the usage of our system constitutes an important step forward for enhancing passenger experience while boarding onto an airplane compared to current boarding approaches. In order to give an overview of the proposed boarding controller Fig. 1 depicts it in terms of block scheme. As it can be noticed, the controller is dependent on both real parameters obtained online and the current state of the system in terms of previously allocated seats. In the following sections we report our results applied without loss of generality to the system presented in [4]. Furthermore, this work is also aimed at proving the technical feasibility of the automatic boarding strategy developed in the above mentioned work.

The main contributions the present work is intended to give are:

- real-time evaluation of passenger and luggage parameters extracted from images after a classification process;
- measure of the reliability in obtaining these parameters in different scenarios.

The rest of this paper is organized as follows. In the second part of this section we provide the related work in classifier-based object and people detection. In Section II we present an overview of the theory behind the developed boarding method. Section III is dedicated to the experimental setup: employed hardware and software architectures are

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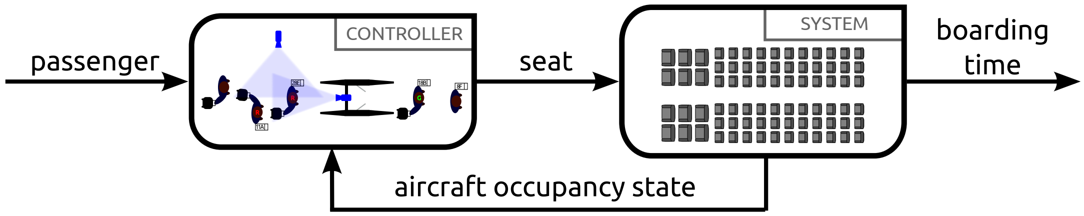


Fig. 1. Block scheme of the considered online boarding strategy. When the passenger arrives at gate, she/he is scanned by vision sensors to retrieve her/his agility and luggage size. By using these data, the controller is able to output the passenger seat taking into account the current state of occupancy of the airplane. The overall output is the resulting reduced boarding time.

explained in detail. Section IV is related to the results of the experiments, mostly focused on proving the reliability of the proposed system in correctly obtaining the input parameters required by the algorithm. Section V concludes the paper and discusses possible future developments.

A. Related Work

Since Viola and Jones in [5] introduced a classifier-based object detection for face recognition a lot of work has been done in this field. Dalal and Triggs in [6], looking at the spatial distribution of edge orientations, proposed to use of grids of Histograms of Oriented Gradient (HOG) descriptors for human detection and simple linear SVM for classification, obtaining impressive results on the MIT pedestrian dataset [7]. In the same work, they also introduced a more challenging dataset, *i. e.* the INRIA person dataset. Tuzel *et al.* in [8] presented a new algorithm to detect humans in images but in this case using covariance matrices as object descriptors, improving the results of Dalal and Triggs. Wu and Nevatia in [9] applied combination of HOG and covariance descriptors coming to a cascade structure where each weak classifier corresponds to a local image region, from which several different types of features are extracted. Bégard *et al.* in [10] addressed the problem of real-time pedestrian detection by considering different implementations of the AdaBoost algorithm. In [11] Dollar proposed a learning approach which automatically learns individual component classifiers and combines these into an overall classifier. Mikolajczyk *et al.* in [12] presented a different method for detecting people, dividing the human body into several parts and applying a cascade of detectors for each part. Feature selection and the part detectors are learned from training images using AdaBoost. Most applications deal with pedestrian ([13], [14]) and vehicle detection ([15], [16]) in autonomous driving field ([17], [18]). Spreeuwers *et al.* in [19] proposed a face recognition system for automatic border control. Other applications can be found in the works of Beymer *et al.* [20] and Buch *et al.* [21]. A comprehensive overview of people detection techniques can be found in [13]. Using these techniques we aim at evaluating two parameters, namely agility and hand luggage coefficients, essential for the online seat allocation algorithm. Regarding the former, currently, there is not a universal accepted definition. A review about different techniques for evaluating agility can be found in [22]. It has been defined as the ability to change direction rapidly [23], [24] or the ability to change direction rapidly and accurately [25], [26]. Some authors have given a definition of agility including not only whole-body change of direction but also rapid movement and direction change of limbs [27]. More recently a more detailed definition has been given by [22] describing the agility as a rapid whole-body movement with change of velocity or direction in response to a stimulus. Using people detection and shape recognition techniques the agility coefficient and luggage size can be calculated as explained in the following section.

II. Review of the Algorithm

In this section the operating principles of the seat allocation algorithm are presented. The main parameters that have been used here and the methods adopted to retrieve them are explained in detail. Then the usage of these parameters for the proposed seats allocation approach is presented. In our system, passengers are classified by means of an *agility* coefficient, from now on indicated by α, and a *hand-luggage* coefficient, referred to as β, used to evaluate the optimal seat for each coming passenger. A computer vision algorithm acquires these parameters from images performing shape recognition of both the passenger and her/his luggage. Images streamed by a camera sensor are classified making use of simple rectangular features based on Haar basis functions [28]. The following procedure is used in order to obtain information from images: first, an offline feature-based classifier is trained for both people and luggage detection; then, we use the trained algorithm to classify the input images and extract two-dimensional geometric features; finally the α and β coefficients are calculated.

A. Agility Coefficient

In order to make the agility detection simpler and suitable for real-time operations, the idea is to quantify the agility by monitoring the variation over time of the modulus and the direction of the velocity vector applied to the Center of Gravity (CoG) of people during their motion (see Fig. 2). We considered the people CoG coincident with the center of the rectangle surrounding the detected body shape. Three images are needed to be processed in order to relate the index α with the acceleration vector modulus and the variation of the velocity vector direction. To detect the velocity vector in space, two cameras (frontal and lateral) are employed, one giving images with information in the plane xy, the second one in the plane yz. The axes xyz are those of

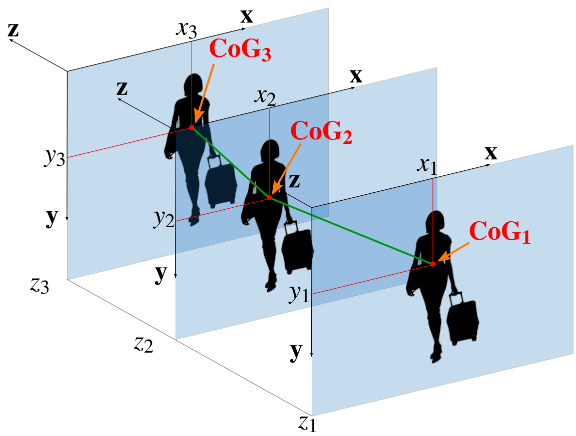


Fig. 2. Measurement of passenger agility starting from Center of Gravity (CoG) displacement in three equally time-spaced frames.

the common reference system adopted for both cameras. The frontal camera follows the CoG in the image plane: the coordinates x_i and y_i represent this in the xy plane. These vary little in the three shots and their change is also due to the perspective transformation. The most significant contribution to the velocity vector is the velocity in the z direction detected by the lateral camera, whose role is more relevant for detecting agility. The coordinates x_i come from the frontal camera, while y_i and z_i from the lateral one. Eq. (1) shows the evaluation of the two velocity vectors, i and $i+1$ which can be obtained from the three images:

$$\begin{aligned}\mathbf{v}_{i,i+1} &= v_{x_{i,i+1}}\hat{\mathbf{i}} + v_{y_{i,i+1}}\hat{\mathbf{j}} + v_{z_{i,i+1}}\hat{\mathbf{k}} = \\ &= \frac{x_{i+1}-x_i}{\Delta t}\hat{\mathbf{i}} + \frac{y_{i+1}-y_i}{\Delta t}\hat{\mathbf{j}} + \frac{z_{i+1}-z_i}{\Delta t}\hat{\mathbf{k}}, \quad i = 1,2.\end{aligned} \tag{1}$$

where Δt is the time interval between consecutive shots, on the order of 100 ms, $\hat{i}$, $\hat{j}$, and $\hat{k}$ are the axis unit vectors. Let θ_x, θ_y and θ_z be the angles between each velocity vector and the x, y and z axis, these can be calculated as in Eq. (2) and used to capture the changes in the orientation of the velocity vector with respect to the reference system:

$$\begin{cases}\theta_{x_{i,i+1}} = \cos^{-1}\frac{v_{x_{i,i+1}}}{|v_{i,i+1}|} \\ \theta_{y_{i,i+1}} = \cos^{-1}\frac{v_{y_{i,i+1}}}{|v_{i,i+1}|}, \quad i = 1,2. \\ \theta_{z_{i,i+1}} = \cos^{-1}\frac{v_{z_{i,i+1}}}{|v_{i,i+1}|}\end{cases} \tag{2}$$

Now, the resulting acceleration vector can be computed:

$$\begin{aligned}\mathbf{a} &= a_x\hat{\mathbf{i}} + a_y\hat{\mathbf{j}} + a_z\hat{\mathbf{k}} \\ &= \frac{v_{x_2}-v_{x_1}}{\Delta t}\hat{\mathbf{i}} + \frac{v_{y_2}-v_{y_1}}{\Delta t}\hat{\mathbf{j}} + \frac{v_{z_2}-v_{z_1}}{\Delta t}\hat{\mathbf{k}},\end{aligned} \tag{3}$$

The vector $\dot{\theta}$ whose components are associated with the rate of variation of the direction of the velocity vectors is then:

$$\begin{aligned}\dot{\boldsymbol{\theta}} &= \dot{\theta}_x\hat{\mathbf{i}} + \dot{\theta}_y\hat{\mathbf{j}} + \dot{\theta}_z\hat{\mathbf{k}} \\ &= \frac{\theta_{x_2}-\theta_{x_1}}{\Delta t}\hat{\mathbf{i}} + \frac{\theta_{y_2}-\theta_{y_1}}{\Delta t}\hat{\mathbf{j}} + \frac{\theta_{z_2}-\theta_{z_1}}{\Delta t}\hat{\mathbf{k}}.\end{aligned} \tag{4}$$

To compute the desired agility index as useful scalar value, the norm of $\mathbf{a}$ and $\dot{\boldsymbol{\theta}}$ are calculated from Eq. (3) and (4). The resulting agility index α is shown in Eq. (5), where $\tilde{a}$ represents the normalized acceleration norm and $\tilde{\dot{\theta}}$ the normalized speed of variation norm of the velocity directions of the selected passenger:

$$\alpha = \frac{\tilde{a} + \tilde{\dot{\theta}}}{2}. \tag{5}$$

These scalar values forming the index are normalized with respect to ideal parameters coming from tests on young athletic people, assumed as reference for agility (agility equal to 1). Further details are reported in [4].

B. Hand-Luggage Coefficient

The evaluation of the β parameter is shown in Eq. (6)

$$\beta = \tilde{A}, \tag{6}$$

where $\tilde{A}$ is the area of the rectangle that encloses the luggage shape, normalized with respect to the maximum area (550×350 mm) which represents the maximum allowable cross-section of hand-luggage for most airlines. If the passenger is detected without luggage, this parameter is set to 0, while if two pieces of luggage are detected for a single passenger, it is set to 1 anyway.

C. Seat Assignment Algorithm

The algorithm is based on a dynamic seat assignment and it focuses on four elements, evaluated for each passenger:

- passenger agility, indicated by α as in Eq. (5)
- hand-luggage coefficient related to the luggage size, represented by β as in Eq. (6)
- group ID and group dimension, if the passenger belongs to a group
- reserved seat, if the passenger has got one.

If the passenger has got a reserved seat or she/he belongs to a group, it is supposed these information are already printed on the ticket, and they will be given as constraints to the seat allocation algorithm. If the passenger has a reserved seat, that seat, of course, will be assigned. If the passenger belongs to any group, and, if there is already at least another member of the same group on board, the passenger will be assigned to a seat next to her/his fellow traveler. Otherwise in case the passenger is the first of the her/his group, the algorithm will find the number of near seats, according to the group size, as more in the back of the airplane as possible. Since usually people belonging to the same group board together, the interference with other passengers behind them will be minimized if they are going to sit in the back of the plane.

When the occupancy state of the plane is high there may not be a sufficient number of near seats, so the algorithm will divide the group into subgroups until it is possible, otherwise, in the worst case, an individual seat to each of the group members will be assigned. If the passenger does not belong to any group, neither has got a reserved seat, α and β come into play. To the passengers whose α is higher than a maximum threshold the algorithm will assign the next seat in the Steffen sequence [29] as more in the back of the airplane as possible. Whereas to the passengers whose α is lower than a minimum threshold the next seat in the Steffen sequence as more in the front of the airplane as possible will be assigned. The maximum and the minimum thresholds have been obtained based on simulation and on a tuning procedure. The values which have been used are: 0.75 for the maximum threshold 0.25 for the minimum threshold. If the value of α is between the two boundaries, the algorithm will take into account also the value of β and the assignment will follow the same logic explained for α. If even β is between the two boundaries the seat assigned to the passenger will be the next one in the Steffen sequence. Table I summarizes the explained procedure. See [4] for a comparison between the performances of the described method and the boarding strategies currently adopted in the airports.

III. Implementation

The computer vision algorithms described in the previous sections have been implemented and tested in a real scenario. The evaluated agility and hand-luggage coefficients have been used as inputs to the simulated boarding strategy described in [4].

A. Hardware and Software

The main control unit of the proposed system is a Raspberry PI microcontroller equipped with a 900 MHz quad-core ARM Cortex-A7 CPU and 1GB RAM. This is connected to a PI camera provided with a 5-Megapixel Omnivision OV647 sensor. The maximum frame rate the camera is able to reach is 30 fps. This parameter, however, was limited by the computational time required by the image processing functions. The algorithm continuously analyzes the video stream provided by the camera and outputs the estimated agility value of the detected passenger as well as the hand-luggage coefficient. The developed software is based on the OpenCV C++ library. The people detector uses the HOG technique, provided by the library, while the hand-luggage is detected using a cascade classifier. For testing purposes this has been previously trained using a database of 600 images of passengers, which have been proved to be sufficient to train a working classifier. Fig. 3 shows the employed hardware and software setup.

TABLE I

Logic for the seat assignment

α	β	**Seat assignment logic**
$[0,\ 0.25]$	–	find the seat on the closest *local maximum*
$[0.75,\ 1]$	–	find the seat on the closest *local minimum*
$]0.25,\ 0.75[$	$[0,\ 0.25]$	find the seat on the closest *local maximum*
$]0.25,\ 0.75[$	$[0.75,\ 1]$	find the seat on the closest *local minimum*
$]0.25,\ 0.75[$	$]0.25,\ 0.75[$	assign the next seat in the sequence

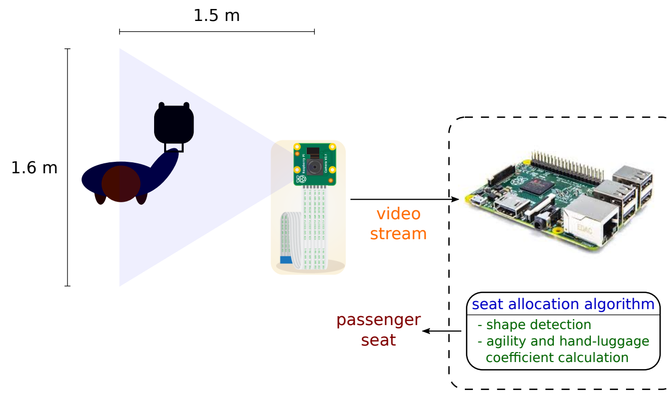


Fig. 3. Hardware and experimental setup.

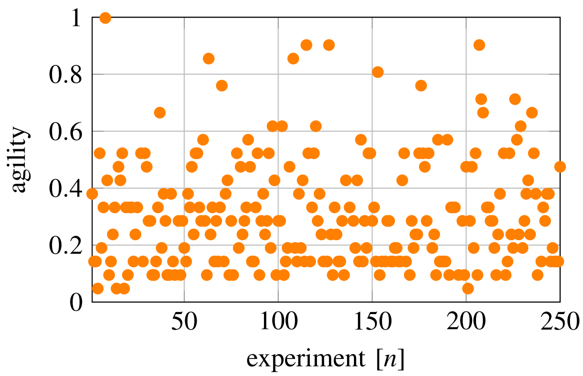
B. Experimental Setup

For the purpose of evaluating the performances of the proposed boarding strategy in real conditions, we performed several experiments using the above mentioned hardware setup. Our main goal was that of demonstrating reliability and adaptability of our system in multiple situations. Hence, we considered three working scenarios in which a different number of people are simultaneously present in front of the camera:

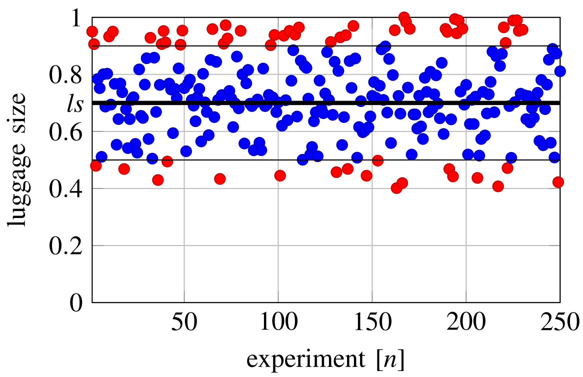
- single person
- queue of people
- crowd.

These experiments are intended to reproduce the usage of the system once installed at the gates in the airports.

During the experiments the camera has been mounted in a fixed position and opportunely oriented towards the place where passengers queue up. In this configuration the camera images contain the passenger and her/his luggage. The described settings are shown in Fig. 3. People participating in the experiments have been also previously instructed to walk in a straight line path according to the particular experimental case. Also because of this reason, only one camera has been employed to evaluate passenger agility. For testing purposes, in fact, the lateral components of the velocity have been neglected, as already explained in Section II-A. A more refined estimation can be obtained considering them in the calculation of the passenger acceleration.



(a) Agility measurements



(b) Detected luggage sizes

Fig. 4. Agility and hand luggage measurements taken on real scenario for different passengers in 250 experiments. In Fig. 4(b) *ls* represents the true luggage size while thinner lines enclose the measurement range of acceptability. Blue marks are accepted values while red marks are retained wrong measurements.

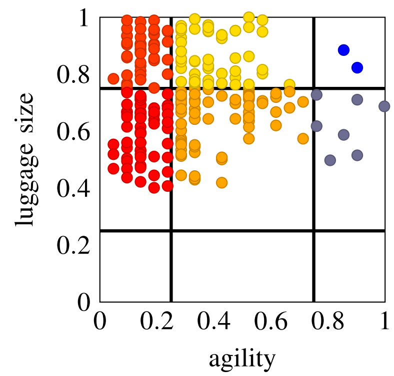


Fig. 5. Passenger grouping based on detected luggage size and measured agility (different colors represent different people categories).

IV. Experiments

This section presents the results of the performed experiments and compares them with the expected ones in terms of reliability of the system. The real experiments constitute an essential validation of our previous work in which randomly generated inputs have been used to compare our boarding method with other existing ones using simulation [4].

A. Single Person

In this experiment our system is in charge of identifying and classifying one person at a time. This is intended to show the system behavior in an ideal situation in which there is no possibility to miss a person or to wrongly associate luggage to passengers like in the other considered cases (queue and crowd). Different people have normally walked through the scene at their own gait. We compared the values of luggage size measured in 250 experiments with the real value previously determined to be 70% of maximum allowed size (labeled as *ls* in Fig. 4(b)). On the other hand, the agility is computed starting from the motion of the passenger while crossing the camera field of view. The measured values for the presented experiments are shown in Fig. 4(a). These values have been then exploited to determine the percentage of succeeded scans. In other words, we compared the measured quantities with the real ones, and accepted the measure as succeeded if it is sufficiently close to the real one. Since no restrictions have been put on the people movements we only considered the luggage measurement. The range of acceptability of the measures is determined by an upper and a lower threshold values expressed in terms of percentage of the real value (thinner horizontal lines in Fig. 4(b)). By choosing $\pm 20\%$ of acceptable error, the results have demonstrated a percentage of reliability of 84%. The variance of the data is 0.0103 assessing the fact that our system can successfully be employed under these working conditions. Finally, Fig. 5 shows the plane agility/luggage size. The square $[0,1] \times [0,1]$ is subdivided into 9 zones according to the threshold values used by the algorithm. The threshold values between the zones are those described in Section II and summarized in Table I.

B. Queue

In order to test the robustness of our system we performed experiments with multiple people simultaneously present in front of the camera. This experiment is intended to show the capability of the system to handle multiple people and luggage detection and provide correct association between them. This constitutes an important step for speeding up the whole procedure since people are not forced to stop before the scanning phase. In most cases a group of three/four people are present simultaneously in front of the camera forming a queue (walking in a straight line). The percentage of reliability of the system in this experiment is set to be the percentage of corrected associations between the person and her/his luggage. The association is computed on the basis of the minimum euclidean distance between each luggage midpoint and each person center of gravity. In our experiments we noticed that this approach never fails or wrongly associates luggage to people so the queue case can be robustly handled by our system.

C. Crowd

The case of crowd, although very uncommon at the gate, has been considered in order to test the capabilities of our system to handle cases of partial occlusions of the scene objects. The same number of people were present simultaneously in the scene with no prearranged walking path to be followed. In this case the percentage of reliability of the system is not comparable with other experiments. We expected that in such situations the percentage of reliability of the system would have sharply decreased. This situation provides us with guidelines towards further developments in which occlusions of both people and hand-luggage have to be considered.

V. Conclusions

In this paper we presented the validation of a passenger seat assignment system that makes use of computer vision to speed up airplane boarding. In order to explain how this system works, the realistic scenario of a boarding process has been recreated. Using images streamed by cameras placed in designed positions, both passenger agility and the size of the hand-luggage have been estimated. These quantities have been used as input to previously developed passenger seat assignment algorithm. To make the calculation of these parameters suitable for real time applications, a fast and robust approach has been developed. The agility is quantified by monitoring the variation over time of the modulus and the direction of the velocity vector applied to the CoG of people during motion. We identified the velocity in the translational direction as the parameter that has the larger influence in the calculation of agility. As regards the size of hand-luggage, it is evaluated considering the area of rectangle that encloses its shape normalized with respect to a threshold value, chosen as the maximum allowable cross-section for most airlines. The performed experiments confirm that our system can correctly handle different cases and is suitable for implementation in real airport scenarios.

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