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X-Ray Baggage Inspection With Computer Vision: A Survey

DOMINGO MERY[1], (Member, IEEE), DANIEL SAAVEDRA[1], AND MUKESH PRASAD[2], (Senior Member, IEEE)

[1]Department of Computer Science, School of Engineering, Pontificia Universidad Catolica de Chile, Santiago 8331150, Chile
[2]Centre for Artificial Intelligence, School of Computer Science, FEIT, University of Technology Sydney, Ultimo, NSW 2007, Australia

Corresponding author: Domingo Mery (domingo.mery@uc.cl)

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ABSTRACT In the last decades, baggage inspection based on X-ray imaging has been established to protect environments in which access control is of vital significance. In several public entrances, like airports, government buildings, stadiums and large event venues, security checks are carried out on all baggage to detect suspicious objects (*e.g.*, handguns and explosives). Although improvements in X-ray technology and computer vision have made many X-ray detection tasks that were previously unfeasible a reality, the progress that has been made in automated baggage inspection is very limited compared to what is needed. For this reason, X-ray screening systems are usually being manipulated by human inspectors. Research and development experts who focus on X-ray testing are moving towards new approaches that can be used to aid human operators. This paper reports the state of the art in baggage inspection identifying three research fields that have been used to deal with this problem: *i)* X-ray energies, because there is enough research evidence to show that multi-energy X-ray testing must be used when the material characterization is required; *ii)* X-ray multi-views, because they can be an effective option for examining complex objects where the uncertainty of only one view can lead to misinterpretation; and *iii)* X-ray computer vision algorithms, because there are a plethora of computer vision approaches that can address many 3D object recognition problems. Besides, this paper presents useful public datasets that can be used for training and testing, and also summarizes the reported experimental results in this field. Finally, this paper addresses the general limitations and show new avenues for future research.

INDEX TERMS X-ray testing, computer vision, machine learning, deep learning, baggage inspection.

I. INTRODUCTION

In the last decades, baggage inspection based on X-ray testing has been established to protect environments in which access control is of vital significance. In X-ray testing, the aim is to analyze or inspect an object under test non destructively using X-rays [1]. There are many other Non-Destructive Testing (NDT) techniques that have been widely used to determine if a test object deviates from a given set of specifications, without changing or altering that object in any way. We can mention, for example, an ultrasound that uses the propagation of ultrasonic waves [2], hyperspectral imaging that captures at different electromagnetic spectra [3], and thermography that uses infrared light to determine the irradiated temperature [4]. However, they are not suitable for baggage inspection because the information they captured is not enough to determine if there are prohibited items in a bag. Since in X-ray imaging, the objects under test have an amount of transparency, in baggage inspection, X-ray testing is the technique that has been used to detect prohibited objects producing good-quality images of the objects that are inside the bags. X-ray testing diminishes the danger of criminal issues, terrorism and undesired breeding of insects or animals that can affect local plants or animals [5]. In several public entrances, like airports, government buildings, stadiums and large event venues, security checks are carried out on all baggage to detect suspicious objects (*e.g.*, handguns and explosives) [6]. Usually, human inspectors are trained to manipulate X-ray screening systems to detect threat objects in carry-on or checked bags. It is often said that *an image is*

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worth a thousand words, nevertheless, this is not the case in the inspection of baggage, when detecting prohibited items in intricate images. The inspection is very complex because the recognition of prohibited objects can be extremely difficult, when they are located in cluttered bags (with occlusion and rotation problems) [7], [8] as illustrated in Fig. 1.

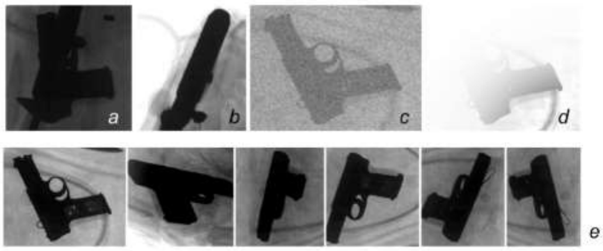

FIGURE 1. Typical problems in the recognition of a gun in baggage inspection: a) occluded gun, b) self-occluded gun, c) noisy X-ray image, d) low quality acquisition, e) different points of views.

In comparison with what is required, the development of automatic tools for baggage inspection is limited and modest. For this reason, human operators are still needed in the manipulation of baggage screening systems [9]. The manual operation of these systems is not only monotonous but stressful and concentration demanding [7]: in a long period only a very low number of threat objects are to be detected, but they have very different shapes and materials, and they need to be recognized in a few seconds. Moreover, inspectors receive only minimal technological support [10]. Even with rigorous training programs, the probability of human mistake gets significant. In the literature is reported that the obtained accuracy by human inspection is between eighty and ninety percent [11].

A general schema for baggage inspection using computer vision is illustrated in Fig. 2. The object under test can be irradiated from different points of view with different X-ray energies. Each block of this diagram can be (or not be) used depending on the application defining different strategies in the solution. For example, there are applications such as knife detection that can be implemented by segmenting a mono-energy single view (black square), or by following a pattern recognition strategy (red squares); or in a cluttered baggage by processing single mono-energy multiview (green squares) or using corresponding information between the views (blue squares); or by processing dual energy X-ray images to establish the material of single views (magenta squares) and multi-views (yellow squares); and finally, solutions that use active vision to find next best projection (cyan squares). For each strategy, the blocks that do not have the mentioned color square are not used.

Automated X-ray testing in this field is less than ideal due to: a) *Loss of generality*: strategies designed for one problem may not be used in another one. b) *Low accuracy*: there is a tradeoff between false positive and false negative rates. c) *Low robustness*, solutions sometimes are robust enough in certain cases only. d) *Low adaptiveness*: a designed cannot be adapted easily to different conditions [12]. Nowadays, in R & D the attempt is made to design new approaches that can support the operation of human inspectors.

This paper identifies three main research areas in the field of X-ray testing that are related to the challenges such as; energies, views and algorithms:

1. **X-ray energies**: there is enough research evidence to show that multi-energy X-ray testing must be used when material characterization is required (*e.g.*, to detect organic products).
2. **X-ray multi-views**: the performance of the examination of a complex object can be better when analyzing multiview (because a single view could present an unrecognizable pose), see for example Fig. 1b.
3. **X-ray computer vision**: there are a plethora of computer vision algorithms that can address many 3D object recognition problems.

This taxonomy is called '3$\mathbb{X}$-Strategy', as illustrated in Fig. 3. Each solution corresponds to a point in the 3$\mathbb{X}$-space, which is defined as a combination of X-ray energies ($\mathbb{X}_1$), X-ray multi-views ($\mathbb{X}_2$) and X-ray computer vision algorithms ($\mathbb{X}_3$).

In the field of baggage inspection, three main factors can have an impact on detection: *i)* the type of X-ray image, which depends on the X-ray energies used in the image acquisition process; *ii)* the point of view, that means the occlusion, which depends on whether or not other objects are superimposed over the target object, and the pose, which is related to the rotation of the object; and *iii)* image complexity, which depends on the number of objects present and how they are placed in the bag. These factors have been addressed using a 3$\mathbb{X}$-strategy: it is clear that certain objects of interest require more than one X-ray energy (*e.g.*, organic materials), more than one view (*e.g.*, razor blades) and more than a simple algorithm (*e.g.*, handguns). In 3$\mathbb{X}$-Strategy for baggage inspection, 'energy' and 'views' are about the X-ray imaging, whereas 'computer vision' is about the recognition algorithm and none is more effective than another, they are just complementary as we will see in the following examples. Thus, for many threat objects, there can be an *ad-hoc* combination of $\mathbb{X}_1$ for energies, $\mathbb{X}_2$ for views and $\mathbb{X}_3$ for algorithms that can be used for its detection. Table 1 provides possible 3$\mathbb{X}$-combinations for certain categories of prohibited items. For example, if we want to identify a flammable liquid in an uncluttered bag (*i.e.*, low image complexity) we need at least dual-energy, possibly only one view, and a simple computer vision algorithm. However, if we want to detect a handgun in a cluttered bag (*i.e.*, high image complexity), we need several views, possibly a computed tomography, and a complex computer vision algorithm. If we want to detect a metallic handgun, dual-energy will be required. A 3$\mathbb{X}$-strategy is to be designed for each kind of object to be detected.

This survey reports how computer vision has been used in baggage inspection identifying three research fields that have been used to deal with the problems such as *i)* X-ray

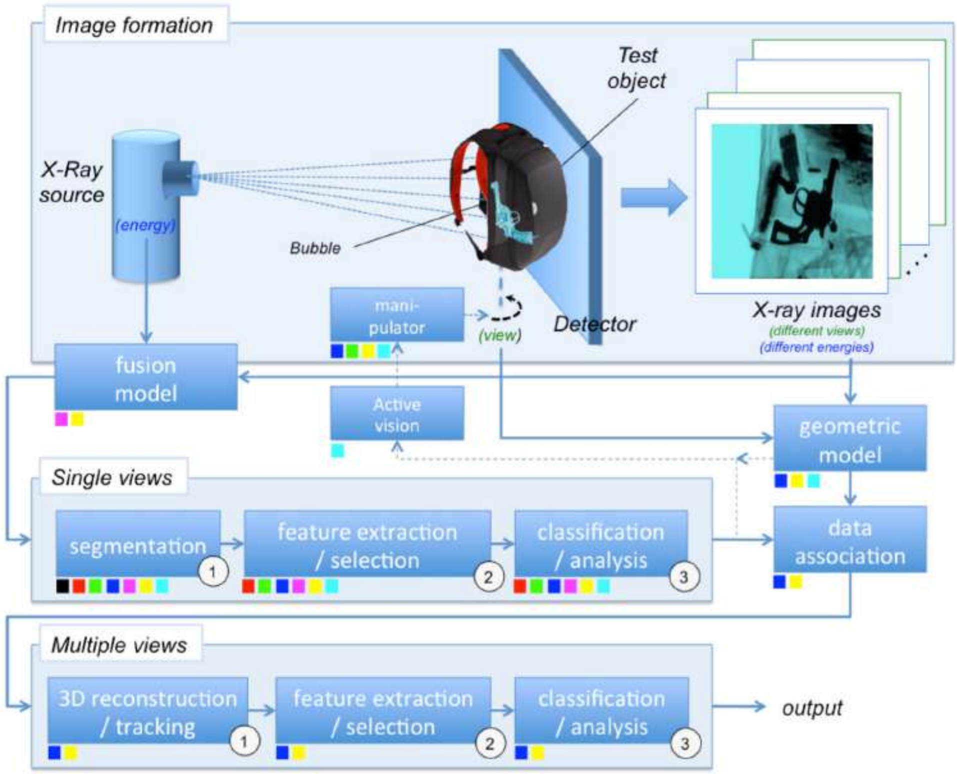

FIGURE 2. General schema for baggage inspection.

TABLE 1. Information on possible combination of energies, views and algorithms for categories of objects.

	$\mathbb{X}_1^*$ Energies 1 2 3	$\mathbb{X}_2^*$ Views 1 2 3	$\mathbb{X}_3^*$ Algorithms 1 2 3
Aerosols	□⊛⊡	⊛⊡⊡	⊛⊡□
Alcohol	□⊛⊡	⊛⊡⊡	⊛⊡□
Ammunition	□⊛⊡	⊛⊡⊡	⊛⊡□
Flammable liquids	□⊛⊡	⊛⊡⊡	⊛⊡□
Fruits & vegetables	□⊛⊡	⊛⊛⊡	⊛⊡□
Guns	⊛⊡□	⊛⊛⊡	⊛⊛⊡
Milk & honey	□⊛⊡	⊛⊡⊡	⊛⊡□
Pepper spray	□⊛⊡	⊛⊡⊡	⊛⊛⊡
Seeds & grains	□⊛⊡	⊛⊛⊡	⊛⊡□
Sharp objects	⊛⊡□	⊛⊛⊡	⊛⊛⊡
Stun guns	⊛⊡□	⊛⊛⊡	⊛⊛⊡
Toxic substances	⊛⊡□	⊛⊡⊡	⊛⊛⊡
Woods & barks	□⊛⊡	⊛⊛⊡	⊛⊡□
*1	mono	mono	simple
2	dual	multi	medium
3	multi	CT	complex

□not used , ⊛used, ⊡probably used

energies (Section II), because there is enough research evidence to show that multi-energy X-ray testing must be used when material characterization is required; *ii)* X-ray multi-views (Section III), because the examination of multiview can increase the performance of the recognition; and *iii)* X-ray computer vision algorithms (Section IV), because there are a plethora of computer vision algorithms that can address many object recognition problems. In this paper, we also present useful datasets of X-ray images for baggage inspection (Section V) and summarize experimental results (Section VI). Finally, we address the general limitations and show new avenues for future research (Section VII).

II. X-RAY ENERGIES ($\mathbb{X}_1$)

There is enough research evidence to show that multi-energy X-ray testing must be used when material characterization is required (*e.g.*, to detect organic products or explosives). In this Section, *i)* we review the principles that govern the X-ray formation of X-ray images with a different kind of energies, we distinguish mono-energy (with only one energy, *i.e.*, grayscale images) from dual-energy and multi-energy (with two or more energies with pseudo-color images), *ii)* we provide some methods that are used when dealing with energies; and *iii)* we address some concluding remarks.

A. BACKGROUND

In non-destructive testing, optical photography of an object under test gives an image of its surface. The photography captures the reflected light. On the other hand, radiography shows the structure that is inside the object by capturing the X-rays that are attenuated when they pass through the object [13]. Although photography and radiography are very different, they share some attributes like noise, perspective, occlusion among others, and computer vision methods that have been developed for optical photographies can be used in X-ray images.

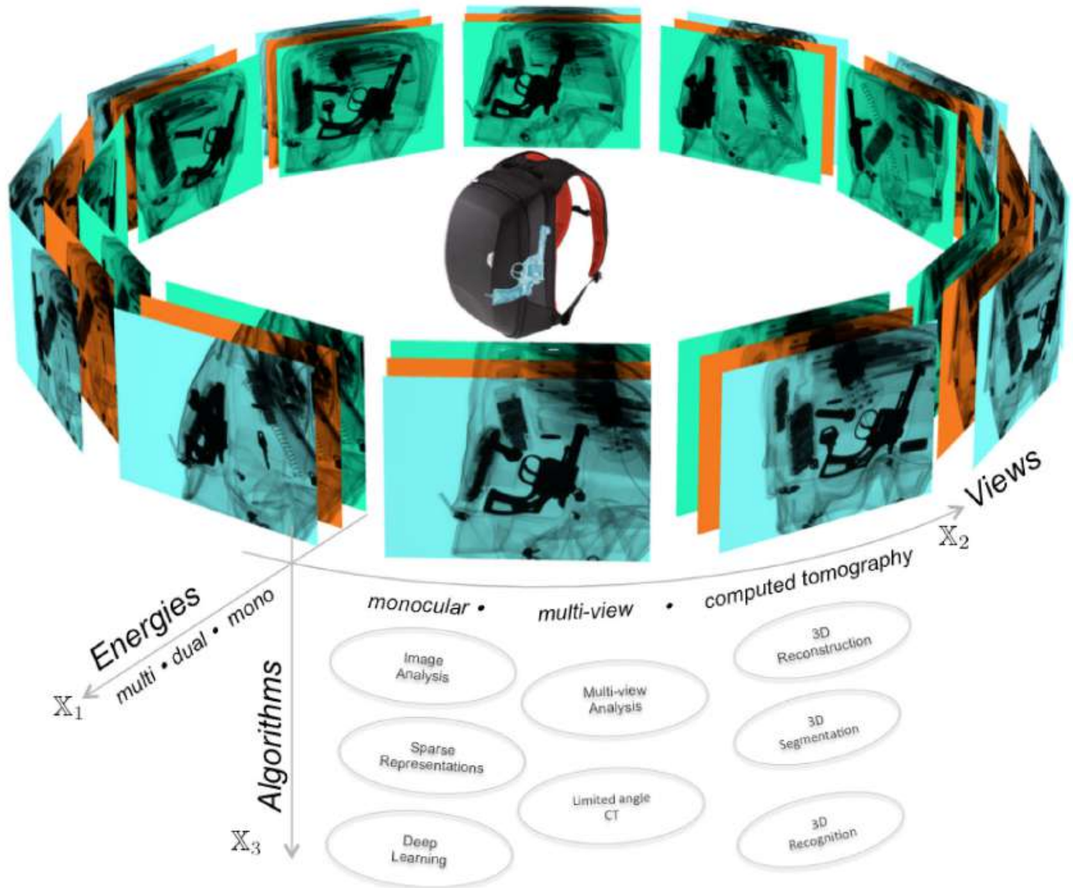

FIGURE 3. 3$\mathbb{X}$-strategy: In 3$\mathbb{X}$-space, a baggage inspection solution is defined as a combination of X-ray energies ($\mathbb{X}_1$), X-ray multi-views ($\mathbb{X}_2$) and X-ray computer vision algorithms ($\mathbb{X}_3$).

The image formation process is illustrated in Fig. 2. The irradiated energy of the X-rays is attenuated following the absorption's law [14]:

$$I = I_0 \exp(-\mu z), \tag{1}$$

where I is the captured intensity as a function of the the thickness z, the emitted intensity I_0, the coefficient μ. Variable μ is the attenuation coefficient that depends on the energy. When the object has n materials (with thickness z_k and coefficients μ_k, for $k = 1, \ldots n$), the captured intensity is modeled as:

$$I = I_0 \exp\left(-\sum_i \mu_i z_i\right), \tag{2}$$

as shown for $n = 3$ in Fig. 4.

In many baggage inspection applications, it is necessary to characterize the material of the objects being tested (typically for organic materials, explosives or drug detection). A material can be identified by estimating it's atomic number Z, which can be calculated using the absorption coefficient μ [15]. When material characterization is required, conventional X-ray imaging (mono-energy) is inadequate because a single value for a pixel (or for a voxel in the case of computed tomography) can barely allow for material identification. It is well known that μ can be expressed as [16]:

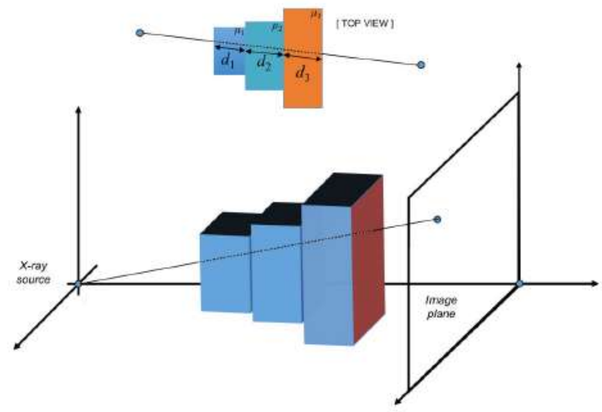

FIGURE 4. Example of the irradiation of an object with three different materials: μ_1, μ_2 and μ_3.

$$\mu = \alpha(Z, E)\rho \tag{3}$$

where Z is the atomic number, E is the energy, ρ is the density and $\alpha(Z, E)$ corresponds to the mass attenuation coefficient in terms of Z and E.[1]

Thus, the material identification (atomic number Z) is determined using more than one X-ray image (with different energies). Only one image is not enough for this task, because the term μz in (1) can be the same for different μz combinations [18]. In a multi-energy system, m X-ray images can be taken with m different energies (where $m > 1$) [19]. In case of dual-energy ($m = 2$), there are two energies: E_1 and E_2 for high and low level [20]. For $i = 1, 2$, we obtain from (1) and (3):

$$I_i/I_0 = \exp(-\alpha(Z, E_i)\rho z), \tag{4}$$

Thus, the following ratio can be estimated as:

$$R = \frac{\ln(I_2/I_0)}{\ln(I_1/I_0)} = \frac{\alpha(Z, E_2)}{\alpha(Z, E_1)} \tag{5}$$

The atomic number Z can be found in public tables (*e.g.*, [21]) using these measurements. A *fusion model* and pseudo-color can be used to generate a new image from Z values [22], [23] (see for example Fig. 5).

B. METHODS

The dual-energy has been used efficiently in several applications (*e.g.*, fat quantification and bone densitometry in medical imaging [19], determination of food density [24], and obviously in baggage screening [18]). However, the aforementioned approach is not enough in certain cases because some organic materials and explosives have similar dual-energy appearances. It is therefore recommended to extract appearance (image) features such as texture features in the recognition of objects with this kind of materials [25].

It is worth mentioning that there are many approaches that use dual-energy in 2D X-ray imaging and computed tomography. In this case, the algorithms consider the estimated material. The reader is referred to as the Sections III-B and IV-B to see those methods.

C. DISCUSSION

We conclude that in certain X-ray applications a unique X-ray image is not enough for recognition and characterization of the material of the test object. Some prohibited objects (*e.g.*, organic materials) cannot be identified using a mono-energy X-ray image. Dual-energy can be considered in material characterization. It would be interesting to experiment with more than two energies to obtain more confident results.

III. X-RAY MULTI-VIEWS ($\mathbb{X}_2$)

The performance of the examination of a complex object can be better when analyzing multi-views (because a single view could present an unrecognizable pose). In this Section, *i)* we present single/multi-views imaging and computed tomography, *ii)* we give some methods that are used in these cases; and *iii)* we address some concluding remarks.

[1] Values for $\alpha(Z, E)$ are available in public tables, *e.g.*, [17]

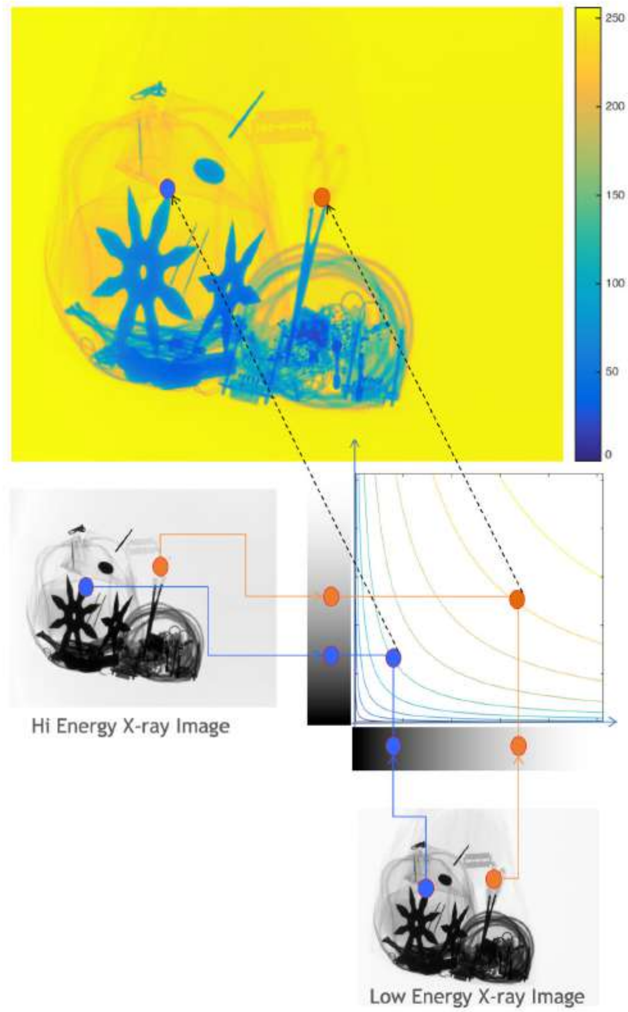

FIGURE 5. Representation of a dual-energy X-ray image using pseudo-color: metallic (blue) and plastic (orange).

A. BACKGROUND

In single view approaches, we usually follow these five steps: *i)* the object under test is located in the desired position and an X-ray image is taken, *ii)* the image is pre-processed (image enhancement, filtering, etc.), *iii)* the object of interest is segmented, *iv)* futures of the segmented part are extracted, *v)* following a pattern recognition schema, the object is classified according to the extracted features. The idea is to determine in the classification, if the object belongs to one of the classes of threat-objects [1].

Since a single view could present an unrecognizable pose, multi-views in baggage inspection could increase the recognition performance [26]. To obtain multi-views of the object, m different projections of the test object can be achieved by rotating and translating it (for this task a manipulator is used). For the k-th projection, for $k = 1 \ldots m$, the 3×4-element matrix P_k, known as the projection matrix, can be used. The parameters of P_k depends on the rotation and translation in 3D of the object, the perspective projection, and scaling, rotation and translation in 2D. The parameters of this model for the m projections are typically estimated following a calibration approach [27].[2] From the projection matrices, bifocal and trifocal tensors are computed [1]. They can be used to establish correspondences between the views, that means, given a point in one view (as a projection of a 3D point), it is possible to estimate where this point is projected into other views.

Another method used in baggage inspection is computed tomography (CT) [30], which produces a cross-section of the object under test. The test object (or the X-ray source) can be rotated to obtain projections at different angles θ. As shown in Fig. 6, for each angle θ a new X-ray intensity profile $I(r, \theta)$ is obtained, where r is the distance to the origin of the object. According to the absorption's law (1) and a parallel-beam geometry, we obtain:

$$I(r, \theta) = I_0 \exp\left(-\int_l \mu(x, y) ds\right) \tag{6}$$

in which (r, s) is a new coordinate system obtained by rotating (x, y) through θ with $x = r\cos\theta - s\sin\theta$ and $y = r\sin\theta + s\cos\theta$. Straight line l is the line of the X-ray beam from the X-ray source to the detector. Thus, the attenuation distribution $\mu(x, y)$, can be computed from all profiles $I(r, \theta)$.

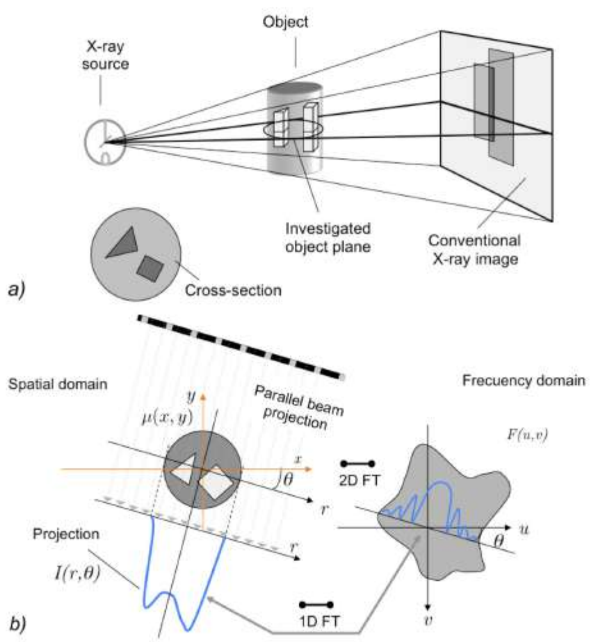

FIGURE 6. Computed tomography (CT) [29]: a) Result of a CT reconstruction. b) Projection slice theorem.

B. METHODS

Several important contributions have been made over the past decades using multiple-view analysis, *e.g.*, motion segmentation [31], 3D reconstruction [32], people tracking [33], object segmentation [34], visual motion registration [35], quality control [36], object class detection [37], and breast cancer detection [38]. Many contributions also have been made using multi-views in X-ray testing [1]. These include for example recognition of regular objects [39], active vision [40], and inspection using dual-energy X-ray [22]. It is worth noting, that the performance is significantly increased by including multi-views. For example, in medicine, it is very useful to analyze an organ from different points of view (*e.g.*, X-ray stereo angiography [41]). The contribution of multi-view analysis is twofold: *i)* 3D features that are estimated from 3D reconstruction and *ii)* 2D corresponding features from multi-views. Both –3D or 2D features in correspondence– are very relevant in object recognition. For example, a 3D reconstruction can be used to measure the geometric dimension of an inner part [42]. Besides, many approaches use dual-energy computed tomography to determine the material of the test objects (see, for example, [19], [24], [43]–[45], to name just a few). On the other hand, 2D features are very useful when validating a detection (from the only view) to filter out false alarms [46].

In computed tomography, in general, a new function $P_\theta(r) = -\ln(I(r, \theta)/I_0)$ is used to calculate the object's cross-sectional plane from the measured projections [30]. The reconstruction of the objective function $\mu(x, y)$ from it's projections presents a typical inverse problem [47]. A great number of algorithms are available, which can be classified into three groups: *i)* Back-projection [48], [49]: This is the most basic method because it simply 'smears' each projection along the path of the X-rays. It allows for a crude reconstruction of the test object. *ii)* Projection-Slice theorem [50]: As illustrated in Fig. 6b, this theorem states that a one-dimensional Fourier transformation of a projection $P_\theta(r)$ at the angle θ is equal to the two-dimensional Fourier transformation of the objective function along a straight line through the origin in Fourier coordinates at the angle θ [51], [52]. A projection $P_\theta(r)$ is obtained through parallel-beam geometry, *e.g.*, by shifting the radiation emitter-detector arrangement radially after each measurement.[3] In practice, however, these ideal conditions cannot be realized. Only a limited number of projection measurements are available for reconstruction, and these are generated from a limited number of line integrals. As such, a two-dimensional function cannot be uniquely defined. *iii)* Filtered back-projection: To avoid the aforementioned problems, this method uses filters with low-pass characteristics. This has a negative impact, especially on high spatial resolution reconstructions, since great discontinuities in the measured values result from the object edges in the projections (highly absorptive material next to

[2] Bundle adjustment algorithm can be used as well. In this approach, the parameters of P_k are estimated from the images themself [28]

[3] Many reconstruction approaches assume parallel-beam geometry, whereas CT scanners usually employ fan-beam geometries. There are dedicated fan-beam algorithms (see for example [53]), however, there are methods that resample the fan-beam data in order to obtain an equivalent parallel-beam data (see, for example, [53]–[55]). Thus, traditional reconstruction approaches can be used.

hollow spaces in the design). This leads to large artifacts, which can make image analysis impossible.

The aforementioned reconstruction problems have been addressed as an ill-posed problem [56]. There are diverse approaches for regularization and optimization algorithms that ensure their convergence. Some consider different *a-priori* information using probabilistic models [57] and geometric models. For example, some models have established a region of interest [58], [59] considering limited angles [60]–[62] or sparse representations [61]–[63], restricting the scope to a binary construction [64], [65], reconstructing faults in homogeneous material [65], or preserving borders [66], [67], to name just a few. The work of Retraint *et al.* [64] merits special interest because the authors conducted a binary reconstruction of the 3D image from just three X-ray projections (not necessarily orthogonal) using an Ising model [68]. Finally, moving away from the aforementioned paradigms and also of interest for this proposal, the work of Prakoonwit and Benjamin [69] must be mentioned. The authors focused on the reconstruction of triangular mesh screens based on few (approximately ten) uniformly distributed views. They propose a method for the definition of 3D 'border' points of the object and 'shape generators' using epipolar geometry [1] and can build more than one object present in a single scene.

C. DISCUSSION

We conclude that the use of multi-views can address many problems in baggage inspection, especially when complex objects cannot be recognized with only a single view. In certain cases, computed tomography is required, whereas in other cases, multi-energy computed tomography can be used. In these cases, one can conclude that solving for the trade-off between the quality of the reconstruction and the number of projections (with the associated time and cost) are still an open problem. There is a great deal of research on reconstructing the 3D object as precisely as possible with diagnostic and object description purposes. The research work has not been found on imprecise 3D reconstructions meant to allow for the recognition of the object without characterization or measurement. For example, in baggage inspection, we are not interested in the accurate size of a knife or details related to its shape. We simply need to know that the object is a knife, or a threat object.

IV. X-RAY COMPUTER VISION ALGORITHMS ($\mathbb{X}_3$)

There are a plethora of computer vision algorithms that can address many 3D object recognition problems. In this Section, *i)* we review the principles that are used in computer vision, *ii)* we give some computer vision approaches used in this field; and *iii)* we address some concluding remarks.

A. BACKGROUND

In object recognition, we distinguish three general families of approaches:

i) Traditional image analysis: In this family, the algorithms are based on traditional image segmentation like detection of edges, histograms, morphology, and filters among others [1]).

ii) Sliding–window: With this approach, we run a small detection window from left to right, and from top to bottom of the image, and in each position we extract features of the portion of the image that corresponds to the detection window. The idea is to design a classifier that distinguishes which windows belong to the object that we are detecting and which not. This approach has been very effective in the computer vision community in the detection of faces [70] and pedestrians [71], and recently in baggage inspection with X-ray images [72].

iii) Deep learning: Solutions based on deep learning have been very successful in the recognition and localization of objects, where handcrafted features were replaced by learned features. Very effective methods have been proposed using Convolutional Neural Networks (CNN) [73], YOLO [74], [75] [76], Faster-RCNN [77], Single Shot Multi Box Detector (SSD) [78], and RetinaNet [79]. The reader can find a survey of object detection approaches based on deep learning in [80].

B. METHODS

In this paper, it is very important to examine the progress made over this decade in baggage inspection and computer vision. In this Section, we give the most important findings in this field.

1) COMPUTER VISION IN 2D

In computer vision, object recognition in 3D from images can be a difficult task (in photography and in radiography as well), not only because objects can be embedded, occluded or deformable, but also there is an unlimited number of points of view, and different acquisition conditions [81].

In baggage inspection with the computer, some algorithms based on the analysis of mono-energy single views have been reported. For example, methods that use sparse representations [82], [83], visual codebooks [84], and logarithmic models [21], [72]. On the other hand, in the analysis of single dual-energy images, the following approaches can be mentioned: Bag of Words (BoW) [23], [85] [86], texture, pseudocolor, edge and shape features [87], [88], Zernike moments [89], Gabor features [25], and SATISϕ features [21]. Additionally, there are some methods based on mono-energy multi-views among which we can highlight: detection based on correspondences in multi-views [39], [46], [90], and active vision [40], [91]. Moreover, in dual-energy multi-views we can find SVM classifiers and visual dictionaries [22], [23], [92], [93].

Finally, methods based on deep learning have been proposed in the last years. In single views using mono-energy and dual-energy images, we can mention [12] and [94], [95] [96], [97] [98] respectively. Besides, there are some contributions based on GAN's (Generative Adversarial Networks) [99] to generate synthetic X-ray images that can be used as data augmentation in the training stage [100], [101].

2) COMPUTER VISION IN 3D

3D image acquisition and reconstruction techniques (3D scanners) have been developed along with the approaches for reconstructing those images by processing multi-views of a single scene. These approaches use 3D data (points, meshes or CAD models) for 3D recognition, where the object under test is reconstructed in 3D, and 3D features are extracted to match them with the 3D features of known 3D objects stored in a gallery [37]. Full reviews of the different approaches that comprise the state-of-the-art can be consulted in [102]–[105]. Following a practical paradigm, the results of benchmarks that evaluate the effectiveness of the existing methods in different contexts are available as well. An international 3D shape recognition competition (SHREC, Shape Retrieval Contest [106]) has been held several times. The most recent reports [107], [108] present a comparison of techniques in the recognition of 60 and 171 categories, respectively. In those benchmarks, the authors concluded that Manifold Ranking [109] and Bag-of-Words [110] methods considering local descriptors of the objects are the state-of-the-art technique for the identification of objects with high intra-class variability. In these benchmarks, several detectors and descriptors are evaluated with promising results (*e.g.*, Harris 3D [111], Mesh-HoG [112], Scale Invariant Spin Image [113], Center-Symmetric Local Binary Pattern (CSLBP) [114]), 3D Shape Context (3DSC) [115], Signature of Histograms of Orientations (SHOT) [116], Fast Point Feature Histogram (FPFH) [117]), and Unique Shape Context (USC) [118].

There has also been an improvement in the field of computed tomography in the examination of luggage. It is worthwhile to mention the following approaches: In [119]–[121], there are some techniques that can be used to reduce metal artifacts, improve the quality and remove the noise of the 3D images. There is some progress in the design of 3D features, for example Zernike [122], [123], RIFT and SIFT [44], [124], and 3D Visual Cortex Modeling [125], [126]. On the other hand, in the field of recognition approaches: random forest [43], [127] and BoW [128]. In cases where the 3D object is partially captures, we can mention the following general approaches (not already used in baggage inspection): salient geometric features [129], signature quadratic form distance [130], visual vocabulary signature [131], salient spectral geometric features [132], shape Google [133] and 'shape dictionary' [134] based on text recovery [135].

FIGURE 7. Image examples of GDXray dataset [136].

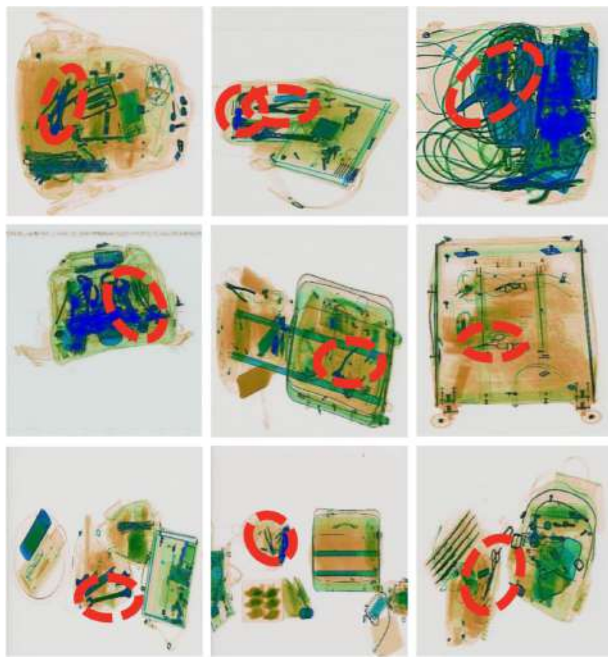

FIGURE 8. Some X-ray images of SIXray dataset [97].

TABLE 2. Public datasets for baggage inspection.

Dataset	# images	Mono	Dual	Classes
GDXray [136]	8.150	Yes	No	Razor blade Shuriken Handgun Knife Spring Clip
SIXray [97]	1.059.231	Yes	Yes	Gun Knife Wrench Plier Scissor Hammer

C. DISCUSSION

We conclude that there is a high level of interest in the scientific world in the recognition of objects through their 3D representations due to the promising applications that have this as their point of departure. It is worth noting that there are methods that are capable of recognizing 3D objects subjected

TABLE 3. Experimental evaluation of X-ray images for baggage inspection.

Ref Year	Dataset	$\mathbb{X}_1^*$ Energies 1 2 3	$\mathbb{X}_2^*$ Views 1 2 3	$\mathbb{X}_3^*$ Algorithms 1 2 3	Experiments	Reported Performance
[139] - 2008	Private	☒☐☐	☒☐☐	☒☐☐	40 handguns 400 non-handgun	not given
[84] - 2016	GDXray	☒☐☐	☒☐☐	☐☒☐	100 razor blades 100 shuriken 200 handguns	AUC 99.17% TPR 98.49% FPR 3.5%
[98] - 2018	GDXray	☒☐☐	☒☐☐	☐☐☒	1000 baggages. Classes: handgun, razor, shuriken	Acc 98.42%
[101] - 2018	GDXray	☒☐☐	☒☐☐	☐☐☒	1329 baggages with razor blade. 822 baggages with guns 540 baggages with knife. 978 baggages with shuriken	Pr 93%, Re 98% Acc 98.4%
[140] - 2019	GDXray	☒☐☐	☒☐☐	☐☐☒	96/766 NB/B* with razor blade. 1671/102 NB/B with knife 160/595 NB/B with handgun. 426/455 NB/B with shuriken	mAP 91.5%
[141] - 2019	Private	☒☐☐	☒☐☐	☐☐☒	662 baggages Classes: bottle, knife, scissor	mAP 86.42 ± 1.19% Re 87.7 ± 0.01%
[23] - 2011	Private	☐☒☐	☒☐☐	☐☒☐	52 baggages with handguns 156 baggages without handguns	mAP 65% Pr 26% , Re 70%
[85] - 2013	Private	☐☒☐	☒☐☐	☐☒☐	850 firearms 10000 non-firearms	TPR 99.07% FPR 4.31%
[95] - 2018	Private	☐☒☐	☒☐☐	☐☐☒	11627 baggages. Classes: camera, gun component gun, laptop , knife, ceramic knife	mAP 88.5%
[97] - 2018	SIXray	☐☒☐	☒☐☐	☐☐☒	2505 baggages with gun. 1554 baggages with knife 1759 baggages with wrench. 3169 baggages with piers 786 baggages with scissors. 840242 negative samples	mAP 38.74% Localization Acc 32.28%
[142] - 2019	Private	☐☒☐	☒☐☐	☐☐☒	4770 mobile phones, 1192 power banks, 3787 umbrellas, 698 laptops, 3586 bottles and 5882 keys	mAP 77%
[143] - 2018	Private	☐☒☐	☒☐☐	☐☐☒	3084 baggages. Classes: big/small electronic equipment, knifes, scissors, pressure tank, metal object	mAP 76.68%
[90] - 2013	GDXray	☒☐☐	☐☒☐	☐☒☐	16 per class classes: clip, spring and razor blade	Pr 95% Re 92.5%
[28] - 2014	GDXray	☒☐☐	☐☒☐	☐☒☐	16 per class classes: clips, springs, razor blades and others	Test 1: Pr 95, 7%, Re 93.9% Test 2: Acc 96.5%
[22] - 2012	Private	☐☒☐	☐☒☐	☐☒☐	435 baggages with handgun 78 baggags without handgun	mAP 64.5%
[144] - 2018	Private	☐☒☐	☐☒☐	☐☐☒	358 baggages with glass bottle 1944 baggages with handgun	mAP 95.56%
[145] - 2019	GDXray	☒☐☐	☐☐☒	☐☒☐	19 baggages, 2 handguns	Pr 91%, Re 91%
[146] - 2013	Private	☐☒☐	☐☐☒	☐☒☐	284 target volumes of handguns and 534 target volumes of bottles	Handguns: TPR 97.3%, FPR 1.8% Bottles: TPR 89.3%, FPR 3.0%
[93] - 2015	Private	☐☒☐	☐☐☒	☐☒☐	335 baggages with handguns 125 baggages with laptops 140 baggages with glass bottles 401 baggages with other objects	mAP 72.03%
[147] - 2015	Private	☐☒☐	☐☐☒	☐☒☐	609 testing images of baggages with bottles, knives, grenades, guns, cellphones	AUC 97.1%
[148] - 2015	Private	☐☒☐	☐☐☒	☐☒☐	baggages with 21 revolvers	TPR 90.5%, FPR 0%
[149] - 2019	Private	☐☒☐	☐☐☒	☐☒☐	101 target volumes of handguns and 88 target volumes of bottles	Handguns: TPR 97.6%, FPR 1.3% Bottles: TPR 98.6%, FPR 1.6%
	*1 2 3	mono dual multi	mono multi CT	simple medium complex	NB/B: image without background and with background, respectively	Pr: Precision, Re: Recall TPR/FPR: True/False positive rate AUC: area under ROC-curve ROC mAP: mean average precision

to various transformations that could solve the problem of the recognition of objects with imprecise reconstruction and occlusion in carry-on bags. Nowadays, it is clear that deep learning recognition approaches have been established themselves as state-of-the-art in this field. In the future, we should explore deep learning approaches on 3D data (when the whole object and only a part of it are available).

V. DATASETS

The datasets for baggage inspection are not as common as for photographic imaging (see for example large-scale datasets of color images in [137] and [138]). Also, some datasets of X-ray images that have been used by the scientific community are not publicly available, because the X-ray images belong to certain security agencies and the authors do not have the permission to distribute. In this Section, we present only those datasets that are free and publicly available. Researchers might use the datasets for educational or research purposes. A summary of the datasets is presented in Table 2.

A. GDXray

This public dataset consists of 19,407 images [136] (some examples are shown in Fig. 7). GDXray is organized in 5 groups: baggage, castings, welds, natural objects and calibration objects. For baggage inspection, there are 8,150 X-ray images (mono-energy X-rays). This group has 77 subsets, and each one has in average 105 X-ray images. In general, the subsets are labeled or annotated giving the bounding boxes of the threat object that are present in the X-ray images. In GDXray, the objects that are present are: razor blades, handguns, shuriken (ninja stars), knives, clips and springs. GDXray has not only X-ray images of travel bags, but also X-ray images of isolated objects that are located in inside a sphere of expanded polystyrene (EPS) (see for example an X-ray image of an isolated ninja star in Fig. 7). Thus, the images of isolated objects can be used in training strategies.

B. SIXray

SIXray is a very large-scale dataset with 1,059,231 dual-energy X-ray images. Fig. 8 shows some X-ray images of the dataset. SIXray contains 6 classes and 8,929 threat objects. SIXray images have been captured in real-world (and complicated) scenarios. In this dataset, only less than 1% of the images has positive labels. In the dataset, the images are colored according to the materials of the objects under test. The images include a large variety in scales and points of view, occlusion and cluttered backgrounds.

C. DISCUSSION

The availability of public databases that can be used for baggage inspection is very limited. While in some areas of computer vision (e.g, face recognition) there are hundreds of databases since the 1990s, in baggage inspection there are the only two public datasets mentioned in previous sections: GDXray and SIXray. The first one consists of a dataset of mono-energy X-ray images captured on controlled scenarios using only one X-ray system (in an X-ray Lab), whereas the second one has dual-energy X-ray images captured in more challenging scenarios (real world) from many different X-ray systems. For these reasons, results are reported on only one of the datasets and cannot be fairly compared. The rest of the datasets used in the experiments reported by the industry and academia are private. In many cases, the entities (industry, government, or academia) that fund research in X-ray testing does not allow databases to be made public. Sometimes this happens for security reasons or perhaps to prevent competitors from having access to data that could improve their processes. Unfortunately, it is not possible to use private datasets to make comparisons and analyses of different computer vision algorithms.

VI. EXPERIMENTAL EVALUATION

This Section shows a comparison of the results of the latest research in baggage inspection. In Table 3, we present each of the work, together with the type of data set, energies ($\mathbb{X}_1$), views ($\mathbb{X}_1$), algorithm complexity ($\mathbb{X}_3$), number of training images, categories used in the investigation, finally the results obtained by these algorithms.

It can be seen that around half of the studies are developed in private datasets, which impedes their easy replication and future comparison with new methods. On the other hand, the type of image depends mainly on the availability of and ad-hoc equipment X-ray imaging system. As discussed in sections II and III, for robust object detection, multi-view samples with dual-energy should be used. Unfortunately, there is still no public database of this style. Moreover, training and testing set are completely different between the works that are using the same dataset, which makes a fair comparison between the different methods impossible. In the same way, the results obtained are presented in different metrics, only the latest research provides the mean average precision metric (mAP), recently used to compare the performance in detection problems.

We conclude that although in recent years several results have been obtained for this particular problem, the lack of public databases or competencies that provide standardized experiments make it extremely difficult to compare the performances of the proposed methods, and consequently know the authentic advances in this area.

VII. CONCLUSION AND FUTURE RESEARCH

In recent years, modern computer vision techniques based on object recognition have been developed in X-ray testing. Many of these methods are making good progress in object recognition, however, they are less than ideal due to many complex problems in X-ray imaging such as clutter, noise, acquisition, and occlusion among others. We observe in this review, that in R & D the attempt is made to design new approaches that can support the operation of human inspectors. The idea of computer vision method is to highlight the potential threat objects on the screen, so the inspectors can make the final decision.

There are still many gaps in the work of baggage inspection, such as; *i)* effective recognition techniques, *ii)* throughput, *iii)* pose difficulty, *iv)* (self)-occlusion, and *v)* image complexity. There are no such learning algorithms available that can address all of these problems. We believe that a solution must efficiently combine X-ray energies, views and computer vision algorithms using the 3$\mathbb{X}$-strategy. This strategy will help human inspectors detect any prohibited items with a reasonable degree of probability.

In comparison with other computer vision applications, we have seen that the introduction of techniques based on modern computer vision for X-ray testing in baggage inspection is very promising, but it has been rather slow. In our opinion, this is due to the construction of public and representative datasets that can be used to train detection models. In baggage inspection using computer vision, the relative number of people working on this task is rather low, and usually, their work is expensive. In this kind of computer vision application, experts are necessary to label the data (make annotations, define bounding boxes, etc). It is very simple to find people that detect bicycles in photographs, however, it is not so easy to find human operators that can distinguish prohibitive objects in a bag by observing an X-ray image. New public datasets with representative cases and good annotations labelled by experts are required in this field.

There is enough evidence that object recognition methods based on deep learning have been established themselves as state-of-the-art in this field, however, it would be interesting to explore deep learning approaches on 3D data (when the whole object and only a part of it are available). Moreover, it would very relevant to investigate the trade-off between the quality of the reconstruction and the number of projections (with the associated time and cost). There is a great deal of research on reconstructing the 3D object as precisely as possible with diagnostic and object description purposes. The research work has not been found yet on imprecise 3D reconstructions meant to allow for the recognition of the object without characterization or measurement. For example, in baggage inspection, we are not interested in the accurate size of a knife or details related to its shape. We simply need to know that the object is a knife, or a threat object.

In baggage screening, where human security plays an important role and inspection complexity is very high, human inspectors are still used. The research that focuses on recognition performed by the humans and machines working in-collaboration is necessary (see for example [148]). This problem raises two main questions: On the one hand, *i)* where are the individual performance frontiers? Can computer vision be better/worse than human vision in certain cases? Or do they have similar performance? On the other hand, *ii)* can computer vision and human vision work in-collaboration to improve their performances? That means, can humans be aided by machines? Or, moreover, can we use human abilities to build better machine learning systems? We believe that human vision and computer vision in recognition can mutually beneficial to each other. That means, *i)* human vision accuracy can be improved if computer vision algorithms can find potential regions with threat objects; and *ii)* computer vision accuracy can be increased if we include new models based on human perception.

As final remarks: *i)* It is recommended to define standard evaluation protocols on public datasets to make fair comparisons. Thus, we can evaluate different strategies to determine easily pros and cons. *ii)* To achieve a high level of trust by the users (passengers, operators, etc.), new developments should be implemented as a trustworthy system. That means, it should be lawful, ethical and robust.[4]

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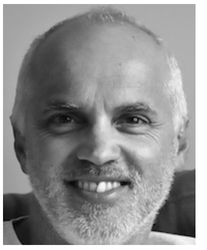

DOMINGO MERY (Member, IEEE) received the M.Sc. degree in electrical engineering from the Technical University of Karlsruhe, in 1992, and the Ph.D. degree (Hons.) from the Technical University of Berlin, in 2000. He was a Research Scientist with the Institute for Measurement and Automation Technology, Technical University of Berlin, with the collaboration of YXLON X-Ray International. He has received scholarships from the Konrad Adenauer Foundation and the German Academic Exchange Service (DAAD). In 2001, he served as an Associate Researcher with the Department of Computer Engineering, Universidad de Santiago, Chile. In 2014, he was a Visiting Professor with the University of Notre Dame. He is currently a Full Professor with the Department of Computer Science, Pontificia Universidad Católica de Chile, where he served as the Chair, from 2005 to 2009, and the Director of Research and Innovation with the School of Engineering, from 2015 to 2018. His research interests include image processing for fault detection in aluminum castings, X-ray imaging, real-time programming, and computer vision. He is the author of 80 technical SCI publications and over 90 conference papers. He was a Local Co-chair of ICCV2015. He received the Ron Halmshaw Award (2005, 2012, and 2017) and the John Green Award (2013) from the British Institute of Non-destructive Testing, which was established to recognize the best articles published in the Insight Journal on Industrial Radiography. He received the Best Paper Award at the International Workshop on Biometrics in conjunction with the European Conference on Computer Vision (ECCV 2014). He is currently serving as an Associate Editor of the IEEE Transaction on Information, Forensics and Security and an Associate Editor of the IEEE Transactions on Biometrics, Behavior, and Identity Science.

DANIEL SAAVEDRA received the B.S. and the M.S. degrees in computer science from the Catholic University of Chile, in 2018 and 2020, respectively. His current research interests include pattern recognition, machine learning, and computer vision for X-ray a testing.

MUKESH PRASAD (Senior Member, IEEE) received the M.S. degree from the School of Computer Systems and Sciences, Jawaharlal Nehru University, New Delhi, India, in 2009, and the Ph.D. degree from the Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan, in 2015. He is currently a Senior Lecturer with the School of Computer Science (SoCS), Faculty of Engineering and Information Technology (FEIT), University of Technology Sydney (UTS), Australia. He worked as a Principal Engineer at Taiwan Semiconductor Manufacturing Company, Hsinchu, from 2016 to 2017. He started his academic career as a Lecturer with the University of Technology Sydney, in 2017. His research expertise includes in the development of new methods in artificial intelligence, machine learning, and data anlytics approache within the domain of computer vision, healthcare, biomedical, the Internet of Things and brain computer interface, and marketing research. He has published more than 100 articles including several prestigious IEEE Transactions and other Top Q1 journals and conferences in the areas of artificial intelligence and machine learning. He is an Associate/Area Editor of several top journals in the field of machine learning, computational intelligence, and emergent technologies.