
X-RAY

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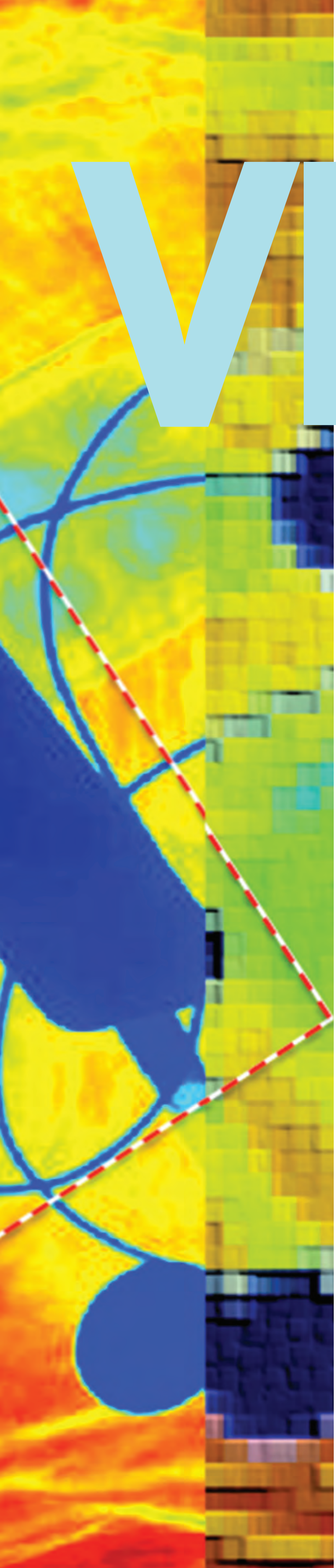

VIEWS

Automated Object Recognition using Multiple X-ray Views

by Domingo Mery and Vladimir Riffo

Editor's Note: This paper is reprinted with permission of the British Institute of Non-Destructive Testing. An earlier version was presented at the 52nd Annual Conference of the British Institute of Non-Destructive Testing, in Telford, England, September 2013 and a paper, "Detection of Regular Objects in Baggage using Multiple X-ray Views," by the authors and two co-authors appeared in Insight – Non-Destructive Testing and Condition Monitoring, *Vol. 55, No. 1, January 2013, pp. 16-20(5). Some additions and edits have been made since by the authors.*

The ability to automatically and robustly recognize objects can be critical for many applications such as surveillance, video forensics, X-ray testing and medical image analysis for computer-aided diagnosis, to mention just a few. This paper is dedicated to automated X-ray object recognition in baggage screening. As X-ray images are taken under controlled conditions, X-ray object recognition may be considered an easy-to-solve problem. This is in contrast with other computer vision problems related to the real world under uncontrolled conditions, for example, people detection or scene recognition (Dollár et al., 2011; Torralba et al., 2008). However, this is not the case for baggage screening, where computer vision techniques are still not effective enough to be used without human interaction (Wales et al., 2009).

In this paper, the authors review certain advances achieved by their research group in this field based on computer vision and machine learning techniques in order to deal with the problem of object recognition. The techniques analyzed multiple X-ray views, because it can be a powerful tool for examining complex objects in cases where uncertainty can lead to misinterpretation. In this approach, multiple views (taken from fixed points of view or using an active vision approach in which the best views are automatically selected) were analyzed in the detection of regular objects.

The rest of the paper is organized as follows: the second section shows a literature overview on baggage screening; the third section presents the approaches that the group has developed in this field; and the fourth section gives some concluding remarks. A preliminary version of this paper was presented elsewhere (Mery and Riffo, 2013).

State of the Art

Since the 11 September attacks, automated (or semi-automated) 3D recognition using X-ray images has become an important element in baggage screening. The inspection process, however, is complex, basically because threatening items are difficult to detect when placed in close-packed bags, superimposed by other objects, or rotated, showing an unrecognizable view (Zentai, 2008). In baggage screening, where human security plays an important role and inspection complexity is very high, human inspectors are still used. Nevertheless, during peak hours in airports, human screeners have only a few seconds to decide whether a bag contains a prohibited item, and detection performance is only approximately 80 to 90% (Michel et al., 2007).

Before 9/11, the X-ray analysis of luggage mainly focused on capturing images of their content. The reader can find in an outside work an interesting analysis carried out in 1989 of several aircraft attacks around the world and the existing technologies to detect terrorist threats based on thermal-neutron activation, fast-neutron activation and dual energy X-rays used in medicine since the early 1970s (Murphy, 1989). In the 1990s, explosive detection systems were developed based on X-ray imaging (Murray and Riordan, 1995). Computed tomography through elastic scatter X-ray comparing the structure of irradiated material against stored reference spectra for explosives and drugs was also developed at that time (Strecker, 1998).

All these works were concentrated on image acquisition and simple image processing; however, they lacked advanced image analysis to improve detection performance. Nevertheless, the 9/11 attacks increased the security measures taken at airports, which in turn stimulated the interest of the scientific community in the research of areas related to security using advanced computational techniques.

Over the last decade, the main contributions were:

- Analysis of human inspection (Wales et al., 2009);
- Pseudo-coloring of X-ray images (Abidi et al., 2006; Chan et al., 2010);
- Image processing techniques, for example, enhancement and segmentation of X-ray images and detection of threatening items in X-ray images, based on texture features, such as detecting a 9 mm automatic machine pistol (Oertel and Bock, 2006; Singh and Singh, 2005);
- Classification techniques, for example, neural networks and fuzzy rules (yielding approximately 80% of performance), and support vector machines for detecting guns in real time (Liu and Wang, 2008; Nercessian et al., 2008).

Other advancements include the use of dual energy (Mery, 2013). This includes dual energy with:

- A background-subtraction-based noise reduction technique (Chen et al., 2005);
- A structural segmentation technique based on attribute relational graph matching (Ding et al., 2006);
- A classification approach based on shape context descriptor and Zernike moments (Mansoor and Rajashankari, 2012);
- An integrated approach of image fusion and noise reduction based on wavelet transform (Rahman et al., 2010);
- An analysis of dual energy images (Lu and Connors, 2006).

The use of computer vision approaches was also developed at this time. These include:

- A recognition approach based on a bag of visual words (Bastan et al., 2011);
- An approach based on visual cortex inspired features (Schmidt-Hackenberg et al., 2012);
- A recognition approach based on speed-up robust features (SURF) (Turcsany et al., 2013).

Even though several scientific communities are exploring many research directions, adopting very

3D recognition using X-ray images has become an important element in baggage screening.

Figure 1. Object categories vary considerably in their visual appearance (both between and within categories), as shown in different images from the: (a) gun; and (b) knife categories.

different principles, and developing a wide variety of algorithms for very different applications, automated X-ray object recognition remains an open question because of the large variability of the appearance and shape of the test objects both between and within categories. For example, many different objects belong to the guns and knives categories, as shown in Figure 1.

Furthermore, the large variability within an object sample depends on its points of view. For example, the top view and frontal view of a gun are very different, as shown in Figure 2. In addition, the appearance of a test object can become different due to (self-)occlusion, noise, and acquisition conditions, as illustrated in Figure 3.

In baggage screening, the use of multiple view information yields a significant improvement in performance, as certain items are difficult to recognize using only one viewpoint. As reported in a study that measured the human performance in baggage screening, (human) multiple view X-ray inspection leads to a higher detection performance of prohibited items under difficult conditions; however, there are no

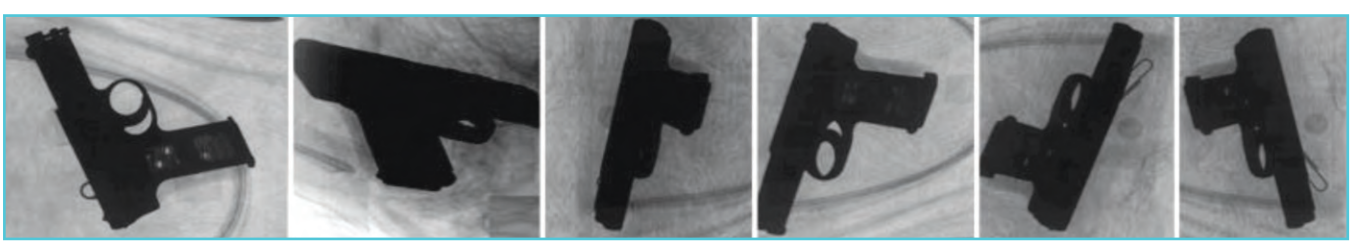

Figure 2. Large variability within a gun: some X-ray images of the same gun in different poses.

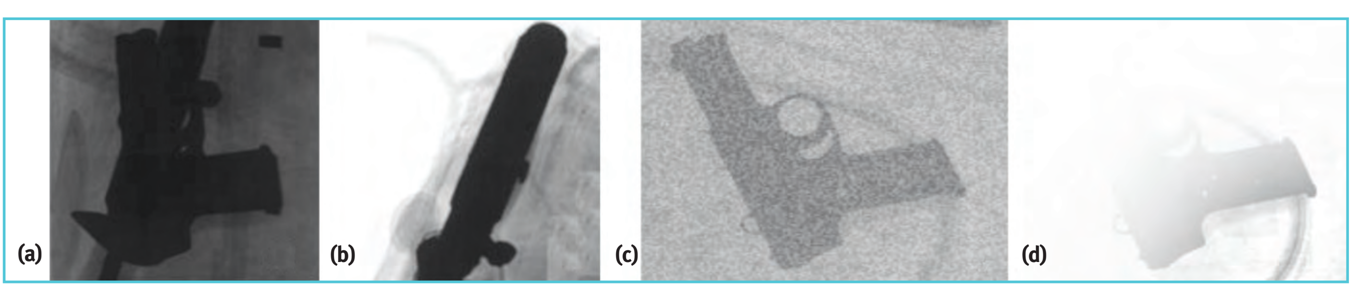

Figure 3. Other problems in recognition of a gun: (a) occlusion; (b) self-occlusion; (c) noise; and (d) wrong acquisition.

significant differences between the detection performance (single versus multiple view) for difficult-easy multiple view conditions. That is, two difficult or two easy views are redundant (von Bastian et al., 2010). The authors observed that for intricate conditions, multiple view X-ray inspection is required.

Recently, some algorithms based on multiple X-ray views were reported in the literature. For example:

- Synthesis of new X-ray images obtained from kinetic depth effect X-ray images based on scale invariant feature transform (SIFT) features in order to increase detection performance (Abusaeeda et al., 2011);
- Analysis of multiple projections of dual energy images using the property of additivity in log space (Heitz and Chechik, 2010);
- Multiple views using standard sliding-window approach with histogram of gradients features (Frenzel et al., 2012);
- Matching in multiple views using an efficient search approach (Bastan et al., 2013).

In the literature review, it was observed that there are few papers on 3D recognition with multiple X-ray views. This paper wishes to contribute to this field.

Techniques Based on Multiple Views

It is well known that an image is worth a thousand words; however, this is not always true if it is an intricate image. In certain X-ray applications, for example, baggage inspection, there are usually intricate X-ray images due to overlapping parts inside the test object, where each pixel corresponds to the attenuation of multiple parts (Mery, 2013).

In some cases, active vision can be used to adequate the viewpoint of the test object to obtain more suitable X-ray images to analyze. Therefore, an algorithm was designed for guiding the manipulator of the X-ray imaging system to poses where the detection performance should be higher (Riffo and Mery, 2012).

In other cases, multiple view analysis can be a powerful option for examining complex objects where uncertainty can lead to misinterpretation. Multiple view analysis offers advantages beyond 3D interpretation. Two or more images of the same object taken from different points of view can be used to confirm and improve the diagnosis undertaken by analyzing only one image. Multiple view analysis in X-ray testing can be used to achieve two main goals: first, analysis of 2D corresponding features across the multiple views; and second, analysis of 3D features obtained from a 3D reconstruction approach. In both cases, the attempt is made to gain relevant information about the test object. For instance, to validate a single view detection—filtering out false alarms—2D corresponding features can be analyzed (Mery and Filbert, 2002). On the other hand, if the geometric dimension of an inner part must be measured, a 3D reconstruction needs to be performed (Noble et al., 1998).

This section summarizes advances achieved by the research group on automated object recognition in baggage screening based on computer vision and machine learning techniques using its X-ray system (see Figure 4). The images tested in the experiments came from the public GDXray database (Mery et al., 2012). The database contains more than 3000 X-ray images for the development, testing and evaluation of image analysis and computer vision algorithms. The database includes three groups of X-ray images: metal objects including castings, welds, razor blades, ninja

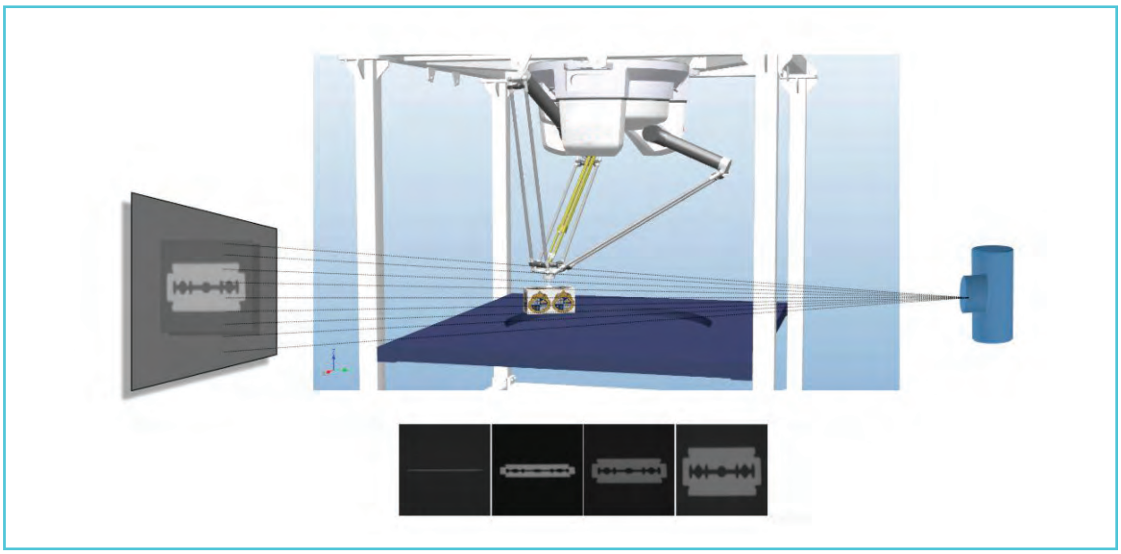

Figure 4. Schematic illustration of the X-ray system: the manipulator can locate the test object in different positions (shown at bottom) in order to analyze different projections.

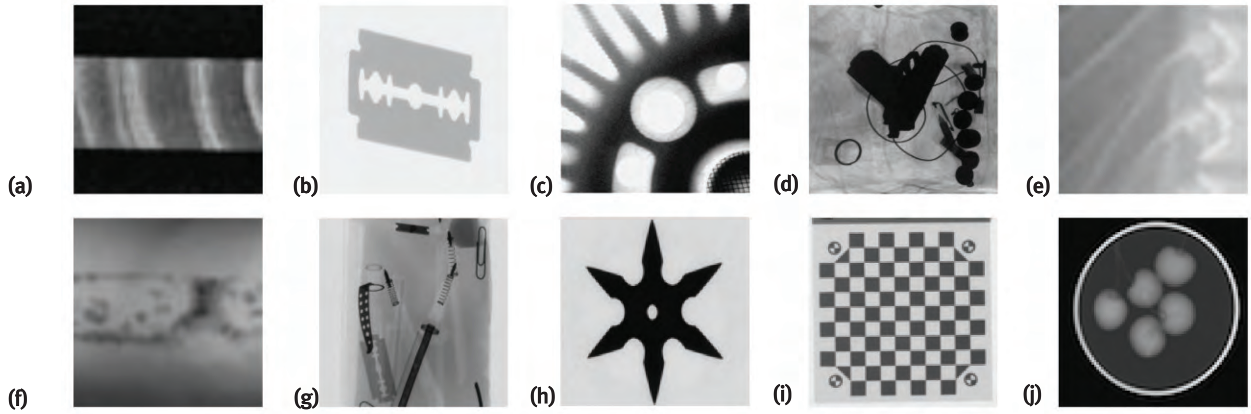

Figure 5. Some X-ray images of the public database GDXray: (a) wood; (b) razor blade; (c) aluminum wheel; (d) bag with a gun; (e) fish bones; (f) weld; (g) pen case; (h) shruriken; (i) calibration pattern; and (j) apples.

stars (shuriken), guns, knives and sink strainers; baggage (bags and pen cases); and natural objects like fruits, fish bones and wood. Some examples are illustrated in Figure 5.

Detection by Tracking Monocular Detections

This section summarizes the multiple view approach outlined in previous work using ad-hoc single view detectors for regular objects (Mery, 2011; Mery et al., 2013). The proposed technique follows two main steps: geometric model estimation, to obtain a geometric model of the multiple views; and parts detection, to detect the object parts of interest.

- Geometric model estimation: this strategy deals with detections in multiple views. In this problem of data association, the aim is to find the correct correspondence among different views. For this reason, multiple view geometric constraints were used to reduce the number of matching candidates between monocular detections. In this approach, the geometric constraints were established from bifocal (epipolar) and trifocal geometry (Hartley and Zisserman, 2003). Thus, for detection in one view it is possible to estimate where its corresponding detection in another view should be. To this end, bifocal tensors (or a fundamental matrix) and trifocal tensors were estimated from projection matrices, which can be computed by minimizing the error between real and modeled projection 3D $\rightarrow$ 2D. This can be done using calibration (Hartley and Zisserman, 2003; Mery, 2003). A bundle adjustment approach can also work (Mery, 2011; Triggs et al., 2000).
- Parts detection: this section gives details of the algorithm that detects the object parts of interest. The algorithm consists of following two main steps: identification and tracking. The strategy is to ensure the detection of the existing parts of interest in the first step, allowing the inclusion of false alarms. The discrimination between both is achieved in the second step using multiple view analysis, where the attempt was made to track the potential parts of interest along the image sequence.

In the identification, potential parts of interest are segmented and classified in each image of the sequence. It is an ad-hoc single view detector that depends on the application. Five segmentation approaches were tested in these experiments:

- Maximally stable extremal regions detects thresholded regions of the image that remain relatively constant by varying the threshold in a range (Matas et al., 2004);
- Spots detector segments regions by thresholding the difference between original and median filtered image (Gonzalez and Woods, 2008);
- SIFT matching detects regions of the image, wherein SIFT descriptors are similar to SIFT descriptors of reference objects (Lowe, 2004);
- Crossing line profile detects closed and connected regions from the edge image that meet contrast criteria (Mery, 2003);
- Sliding windows classifies a detection window that is passed over an input image in both horizontal and vertical directions using a pattern recognition approach (Viola and Jones, 2004).

The general framework attempts to find a "good view" of the inspection object

An existing part of interest can be successfully tracked in the image sequence because its appearance in the images is similar and its projections are located in the positions dictated by geometric conditions. In contrast, false alarms can be successfully eliminated in this manner since they do not appear in the predicted places on the following images and, thus, cannot be tracked. The tracking in the image sequence is performed using algebraic multifocal constraints, bifocal (epipolar), and trifocal constraints among others obtained from the geometric model estimated in the previous step.

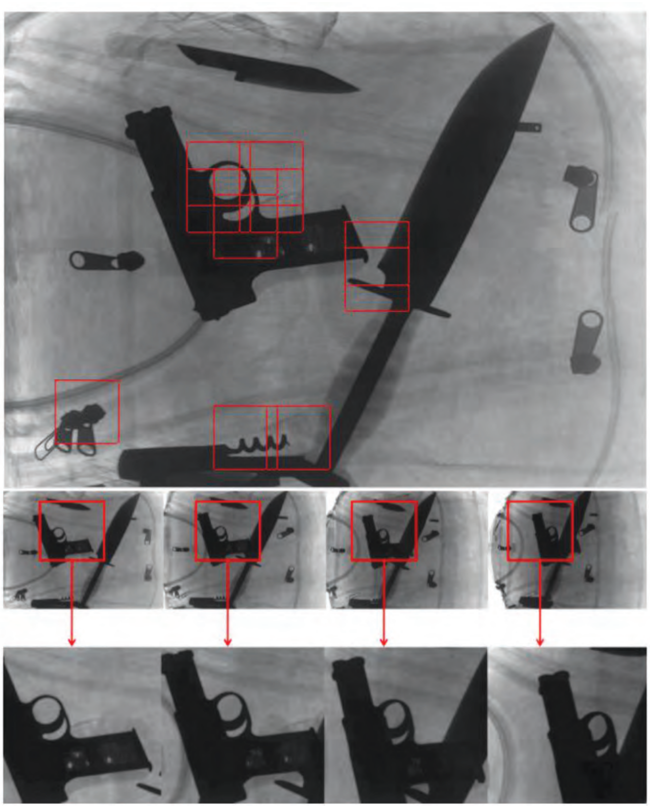

Figure 6. Detection of a gun in a bag: (a) single view detection of a gun, in which several false alarms can be observed; (b) sequence with four X-ray images; and (c) with multiple view analysis false alarms are eliminated without discrimination of the gun.

An example of detection of guns using this approach is illustrated in Figure 6, where a classifier was trained to detect triggers. To demonstrate the effectiveness of the proposed technique, several applications—like detection of pen tips, razor blades, pins and guns in pencil cases or bags—were tested, yielding promising results. Precision and recall were 93% in 34 sequences from 4 to 8 views.

The reader is referred to outside work for a detailed description of the tracking algorithm and more examples (Mery, 2011; Mery and Riffo, 2013).

Active X-ray Vision

An active X-ray testing framework was developed that was able to adequate the viewpoint of the target object in order to obtain better X-ray images to analyze. The key idea of this technique is to automatically adapt the viewpoint of the X-ray images to project the target object in poses where the detection performance should be higher. Thus, the detection inside of complex objects can be performed in a more effective way.

The general framework attempts to find a "good view" of the inspection object, that is, an image in which the target object should be viewed from a good pose that ensures its detection. The good poses of the target object correspond to those from which the acquired view has a high probability of detection. For instance, the good poses of a razor blade correspond to the frontal views. Thus, the key idea is to rotate and translate the inspection object from an initial position to a new one in which the detection probability of the target object should be higher. Clearly, if the initial position corresponds to a good view, no more positions will be required; in these cases the inspection is performed with only one X-ray image.

An example of detection of a razor blade using active vision is shown in Figure 7. In the first view (left column) no blade was detected; for this reason a new point of view was generated. In the second view (middle column), a razor blade was detected; however, the estimated pose did not correspond to a good view. Thus, a new view (right column) was obtained to corroborate the detection. The ability of this approach to find the target object looking for good views even with partial occlusions can be seen.

Two approaches that are able to detect the target object in a single view were evaluated: SIFT matching detects regions of the image in which SIFT descriptors are similar to SIFT descriptors of reference objects; and implicit shape model (ISM) uses a visual vocabulary that is built by clusters of local features and their spatial probability distribution, which has been demonstrated to yield good recognition results for rigid objects (Leibe et al., 2008; Lowe, 2004). Figure 8 shows the detection of a shuriken (commonly known as a ninja star) and a razor blade using ISM.

Using a robotic arm and a semiautomatic manipulator system, the robustness and reliability of the technique were verified in the automated detection of razor blades located inside of nine different objects, showing promising preliminary results. In 130 experiments it was possible to detect the razor blade 115 times with 10 false alarms, achieving a recall of 89% and precision of 92%.

The reader is referred to outside work for a detailed description of the active vision algorithm and more examples (Riffo and Mery, 2012).

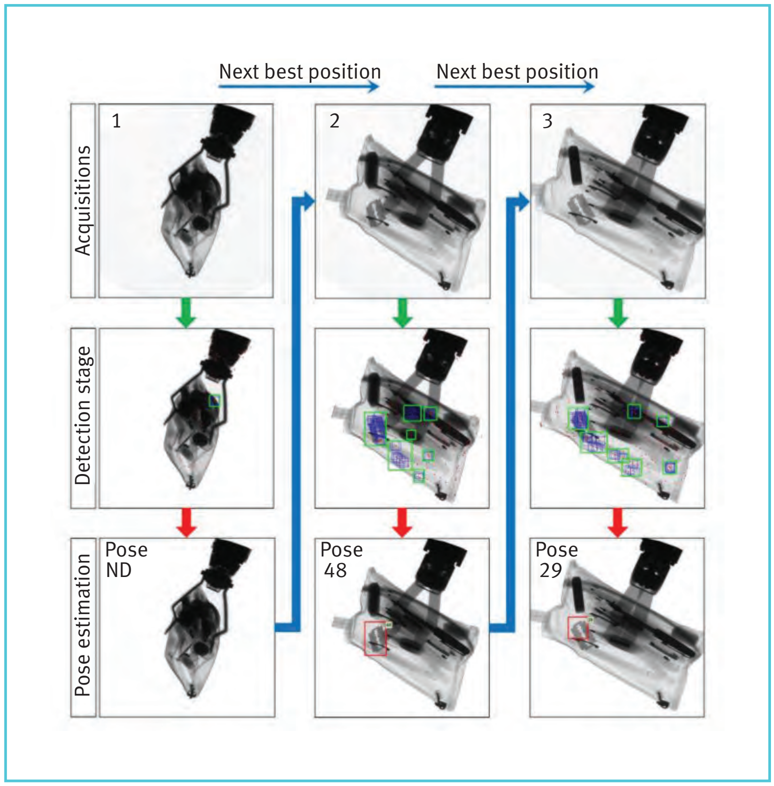

Figure 7. Detection of a razor blade in a pencil case using active vision. ND = no detection.

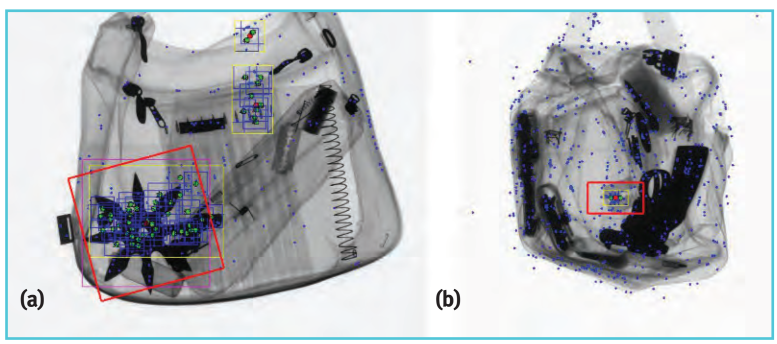

Figure 8. Detection of a: (a) shuriken; and (b) razor blade using the approach based on implicit shape model in a single view (see red boxes).

Recognition using an Efficient Search Algorithm

Recently, a new technique was developed based on multiple X-ray views to recognize certain regular objects with highly defined shapes and sizes. The technique consists of two stages: monocular analysis, to obtain possible detections in each view of a sequence; and multiple view analysis, to recognize the objects of interest using matchings in all views.

- Monocular detection: a classifier, h, was learned to recognize patches or key points of the parts that were being detected. Images were taken of representative objects of each class from different points of view. In order to model the details of the objects from different poses, several key points per image were detected, and for each key point a descriptor, $\mathbf{y}$, was extracted using, for example, local binary patterns, SIFT and SURF, among others (Mikolajczyk and Schmid, 2005). In this supervised approach, each descriptor, $\mathbf{y}$, was manually labeled according to its corresponding class, c. Given the training data ($\mathbf{y}_t$, c_t), for $t = 1, \ldots, N$, where N is the total number of descriptors extracted in all training images, a classifier, h, was designed that maps $\mathbf{y}_t$ to its classification label c_t; thus, $h(\mathbf{y}_t)$ should be c_t. In monocular testing images (see for example Figure 9a) key points are extracted and classified using h. Classified key points are clustered using a mean shift algorithm (Comaniciu and Meer, 2002). Only those clusters that have a large enough number of key points were selected. They are called detected monocular key points, as illustrated in Figure 9b.
- Multiple view analysis: multiple view analysis performs the recognition of objects of interest in three steps. In data association, matchings are found for all detected monocular key points in all consecutive images of the sequence. For each detected monocular key point, the potential matching candidates are efficiently sought in a

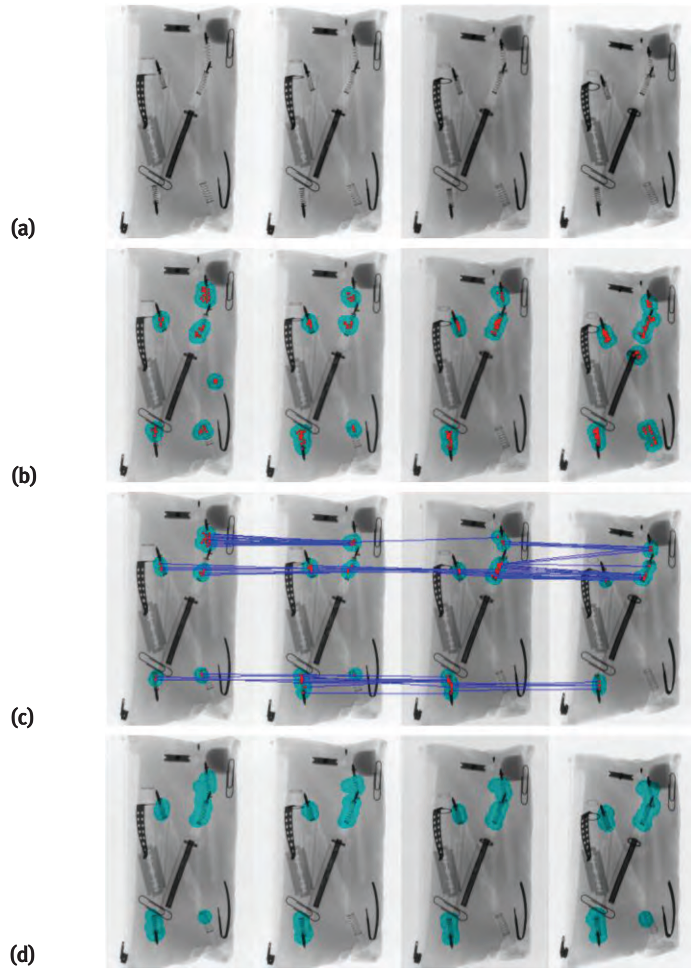

Figure 9. Multiple view detection of springs in a pen case: (a) original test sequence; (b) detected monocular key points; (c) matched key points; and (d) detection.

dense grid of points using a lookup table that is computed off-line as shown in Figure 9c (Mery et al., 2013). Second, during 3D analysis, from each pair of matched key points, a 3D point is reconstructed. Similar to the monocular detection approach, neighboring 3D points are clustered in the 3D space using a mean shift algorithm, and only those clusters that have a large enough number of 3D points are selected (Comaniciu and Meer, 2002). Third, during final analysis, for each selected 3D cluster, all 3D reconstructed points belonging to the cluster are re-projected onto all images. The extracted descriptors of the key points located near these re-projected points are classified individually using classifier *h*. The cluster will be classified as class *c′* if there is a large number of key points individually classified as *c′*, and this number represents a majority in the cluster (see Figure 9d).

This majority vote strategy can overcome the problem of false monocular detections when the classification of the minority fails. A cluster can be misclassified if the part that one is trying to recognize is occluded by a part of another class. In this case, there will be key points in the cluster assigned to both classes; however, it can be expected that the majority of key points will be assigned to the true class if a small number of key points is misclassified. Results with some overlap, where the task was the recognition of springs and clips, are illustrated in Figure 10.

To illustrate the effectiveness of the proposed technique, experimental results on recognizing regular objects—clips, springs and razor blades—in pen cases are shown achieving approximately 93% accuracy for 120 objects.

The reader is referred to a prior work for a detailed description of the active vision algorithm and more examples (Mery et al., 2013).

Conclusion

This paper would like to make a contribution to object recognition in baggage screening. The authors based their techniques on potent ideas such as: detection windows, as they obtain a high performance in recognition and detection problems in computer vision;

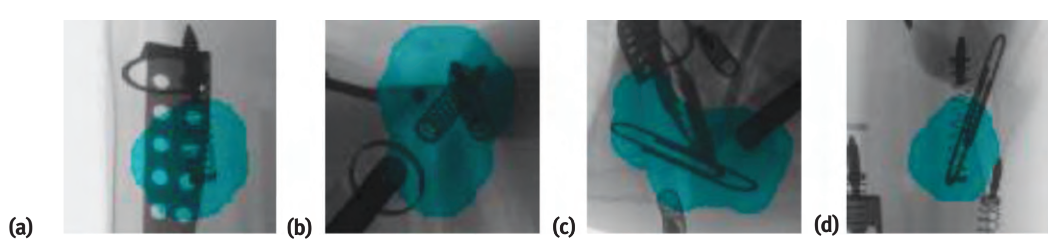

Figure 10. Recognition using the authors' approach in cases with some degree of overlap: (a) one spring; (b) two springs; (c) one clip; and (d) one clip. Each figure shows a part of one image of the whole sequence.

multiple views, as they can be an effective option for examining complex objects where uncertainty by analyzing only one angle of perspective can lead to misinterpretation; efficient visual search, given the speeds involved when searching for objects; and active vision, which is able to adequate the viewpoint of the target object in order to obtain better X-ray images to analyze.

It might be possible to design an automated aid in a target detection task using the proposed algorithms. It has been shown that these preliminary results are promising. However, since the performance of the techniques has been verified on a few radioscopic image sequences, an evaluation on a broader database is necessary.

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