Automated Object Recognition Using Multiple X-ray Views

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Abstract

In order to reduce the security risk of a commercial aircraft, passengers are not allowed to take certain items in their carry-on baggage. For this reason, human operators are trained to detect prohibited items using a manually controlled baggage screening process. The inspection process, however, is highly complex as hazardous items are very difficult to detect when placed in close packed bags, superimposed by other objects, and/or rotated showing an unrecognizable profile. In this paper, we review certain advances achieved by our research group in this field. Our methodology is based on multiple view analysis, because it can be a powerful tool for examining complex objects in cases in which uncertainty can lead to misinterpretation. In our approach, multiple views (taken from fixed points of view, or using an active vision approach in which the best views are automated selected) are analyzed in the detection of regular objects. In order to illustrate the effectiveness of the proposed method, experimental results on recognizing guns, razor blades, pins, clips and springs in baggage inspection are presented achieving around 90% accuracy. We believe that it would be possible to design an automated aid in a target detection task using the proposed algorithm.

Keywords: X-ray testing, object recognition, multiple X-ray views, computer vision applications.

1 Introduction

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. Our 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 as an "easy to solve" problem in comparison with other computer vision problems related to the real world under uncontrolled conditions (*e.g.*, people detection [9] or scene recognition [40]), however, this is not the case of baggage screening, where computer vision techniques are still not effective enough to be used without human interaction [45].

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

The rest of the paper is organized as follows: Section 2 shows a literature overview on baggage screening; Section 3 presents the approaches that our group has been developed in this field; and Section 4 gives some concluding remarks. A preliminary version of this paper was presented in [25].

2 State of the art

Since the September 11 attacks, automated (or semi-automated) 3D recognition using X-ray images has become a very important element in baggage screening. The inspection process, however, is complex, basically because threatening items are very difficult to detect when placed in close-packed bags, superimposed by other objects, and/or rotated showing an unrecognizable view [46]. 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 or not a prohibited item, and detection performance is only about 80-90% [28]. Before 9/11, the X-ray analysis of luggage mainly focused on capturing the images of their content: the reader can find in [30] 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 (TNA), Fast-Neutron Activation (FNA) and dual energy X-rays (used in medicine since the early 70s). In the 90s, Explosive Detection Systems (EDS) were developed based on X-ray imaging [31], and computed tomography through elastic scatter X-ray (comparing the structure of irradiated material, against stored reference spectra for explosives and drugs) [39]. 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

[45], pseudo-coloring of X-ray images [1, 5], enhancement and segmentation of X-ray images [38] and detection of threatening items in X-ray images, based on texture features (detecting a 9mm Colt Beretta automatic (machine) pistol) [34], neural networks and fuzzy rules (yielding about 80% of performance) [15], SVM classifier (detecting guns in real time) [32], and dual energy [23] in single views: using image processing techniques (*e.g.* a background-subtraction-based noise reduction technique [6], a structural segmentation method based on Attribute Relational Graph (ARG) matching [8], a classification approach based on shape context descriptor and Zernike moments [18], an integrated approach of image fusion and noise reduction based on wavelet transform [35], an analysis of dual energy images [17]) and computer vision approaches (*e.g.* a recognition approach based on bag of visual words [4], an approach based on visual cortex inspired features [37], and a recognition approach based on Speed-Up Robust Features (SURF) [42]).

Even though several scientific communities are exploring many research directions, adopting very 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 (*e.g.* to the category *guns* and *knives* belong many different objects as shown in Fig. 1).

Figure 1: Object categories vary considerably in their visual appearance (both between and within categories) as shown in different images from *knife* and *gun* categories using Google Images (`http://images.google.com`).

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

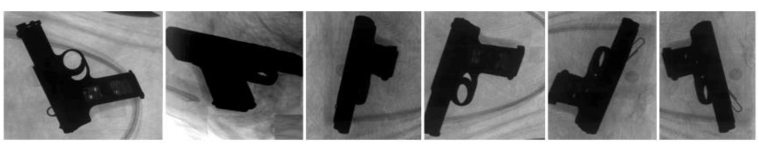


Figure 2: Large variability within a *gun*: some X-ray images of the same gun in different poses.

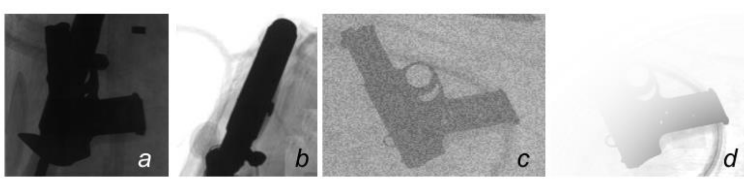


Figure 3: Other problems in recognition of a *gun*: a) occlusion, b) self-occlusion, c) noise, d) wrong acquisition.

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 measures the human performance in baggage screening [44], (human) multiple view X-ray inspection leads to a higher detection performance of prohibited items under difficult conditions, however, there are no significant differences between the detection performance (single vs. multiple view) for difficult-easy multiple view conditions, *i.e.* two *difficult* or two *easy* views are redundant. We 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 (KDEX) images based on SIFT features in order to increase detection performance [2]; and approaches for object detection in multi-view dual-energy X-ray with promising preliminary results (*e.g.* an analysis of multiple projections using the property of additivity in log space [13], multiple views using standard sliding-window approach with HOG features [10], and a matching in multiple views using an efficient search approach [3]).

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

3 Methods based on multiple views

It is well known that *an image says more than thousand words*, however, this is not always true if we have an *intricate* image. In certain X-ray applications, *e.g.* 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 [23].

In some cases, *active vision* can be used in order to adequate the viewpoint of the test object to obtain more suitable X-ray images to analyze. Therefore, an algorithm is designed for guiding the manipulator of the X-ray imaging system to poses where the detection performance should be higher [36].

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 not only in 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: *i*) analysis of 2D corresponding features across the multiple views, and *ii*) 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, in order to validate a single view detection –filtering out false alarms– 2D corresponding features can be analyzed [24]. On the other hand, if the geometric dimension of an inner part must be measured a 3D reconstruction needs to be performed [33].

In this Section, we summarize advances achieved by our research group on automated object recognition in baggage screening based on computer vision and machine learning techniques using our X-ray system (see Fig. 4). The images tested in our experiments come from public GDXray database* [23]. 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 (castings, welds, razor blades, ninja stars (*shuriken*), guns, knives and sink strainers), baggage (bags and pen cases); and natural objects (fruits, fish bones and wood). Some examples are illustrated in Fig. 5.

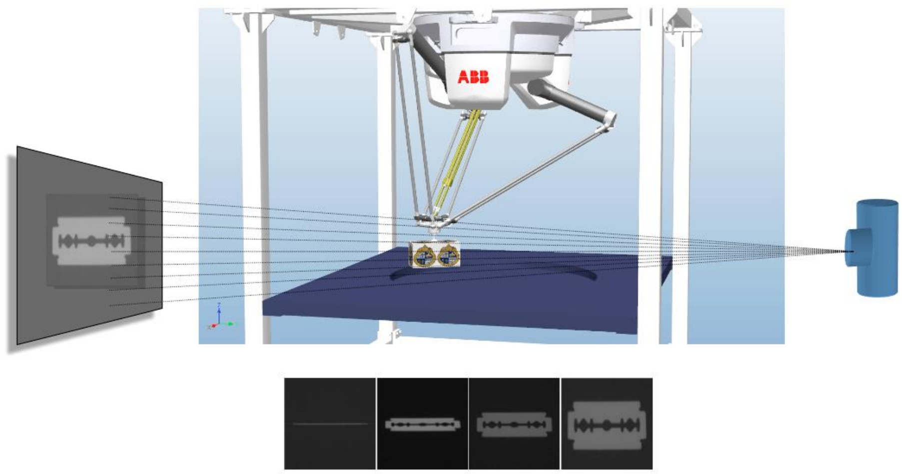


Figure 4: Schematic illustration of our X-ray system: the manipulator can locate the test object in different positions in order to analyze different projections.

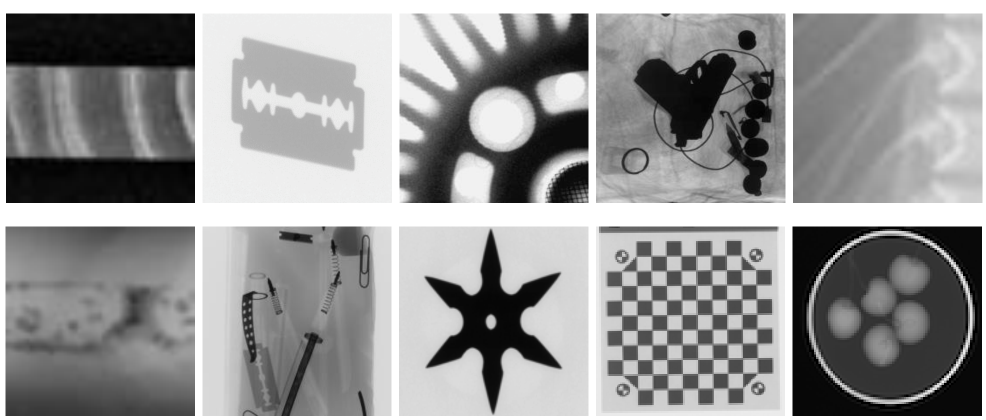


Figure 5: Some X-ray images of our public database GDXray: wood, razor blade, aluminum wheel, bag with a gun, fishbones, weld, pen case, *shruriken*, calibration pattern and apples.

* GDXray: The GRIMA X-ray database. GRIMA is the name of our Machine Intelligence Group at the Department of Computer Science of the Pontificia Universidad Católica de Chile `http://grima.ing.puc.cl`. The X-ray images included in GDXray can be used free of charge, but for research and educational purposes only. Redistribution and commercial use is prohibited.

3.1 Detection by tracking monocular detections

In this Section we summarize the multiple view approach outlined in [22, 26] using *ad–hoc* single view detectors for regular objects. The proposed method 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:** Our 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, we use multiple view geometric constraints to reduce the number of matching candidates between monocular detections. In our approach, the geometric constraints are established from bifocal (epipolar) and trifocal geometry [12]. Thus, for a detection in one view it is possible to estimate where its corresponding detection in another view should be. For this end, bifocal tensors (or fundamental matrix) and trifocal tensors are estimated from projection matrices, which can be computed by minimizing the error between real and modeled projection 3D $\rightarrow$ 2D using *calibration* [12, 21] or *bundle adjustment* [41, 22] approaches.

• **Parts detection:** In this section we give 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 first step, allowing the inclusion of false alarms. The discrimination between both is achieved in second step using *multiple view analysis*, where the attempt is 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 our experiments: *i*) Maximally Stable Extremal Regions (MSER) detects thresholded regions of the image which remain relatively constant by varying the threshold in a range [19]; *ii*) Spots detector segments regions by thresholding the difference between original and median filtered image [11]; *iii*) SIFT matching detects regions of the image which SIFT descriptors are similar to SIFT descriptors of reference objects [16]; *iv*) Crossing line profile (CLP) detects closed and connected regions from edge image that meet contrast criteria [20]; *v*) Sliding windows classifies a detection window that is passed over an input image in both horizontal and vertical directions using a pattern recognition approach [43].

An existing part of interest can be successfully tracked in the image sequence because its appearance in the images is similar and their 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 multi-focal constraints: bifocal (epipolar) and trifocal constraints among others obtained from our geometric model estimated in previous step.

An example on detection of guns using our approach is illustrated in Fig. 6 where a classifier was trained to detect triggers. In order to demonstrate the effectiveness of the proposed method , 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 [22, 26] for a detailed description of the tracking algorithm and more examples.

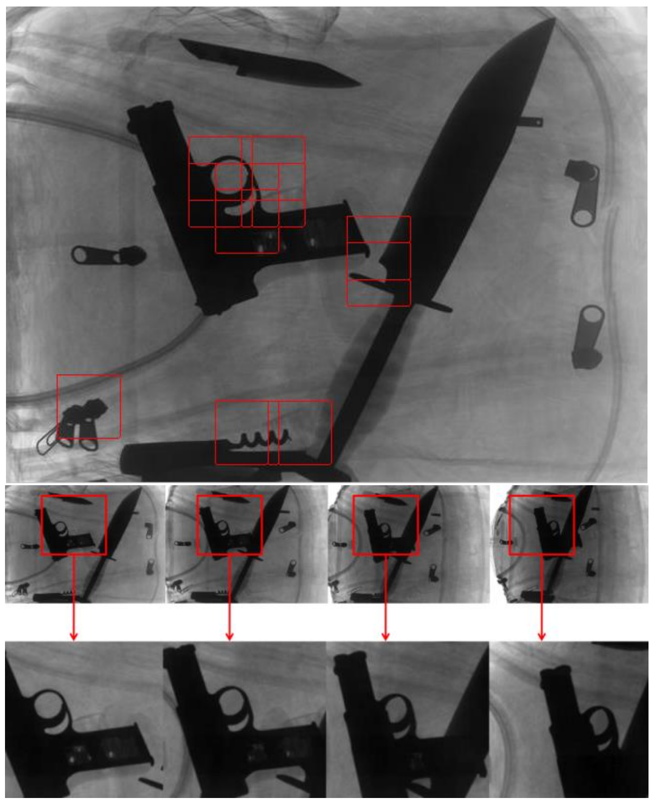


Figure 6: Detection of a gun in a bag. Top: single view detection of a gun, we observe that there are several false alarms. Middle: sequence with 4 X-ray images. Bottom: with multiple view analysis false alarms are eliminated without discrimination of the gun.

3.2 Active X-ray vision

We developed an active X-ray testing framework that is able to adequate the viewpoint of the target object in order to obtain better X-ray images to analyze. The key idea of our method is to adapt automatically the viewpoint of the X-ray images in order 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, *i.e.*, an image in which a target object should be viewed from a good pose that ensures its detection. The good poses of the target object correspond to those ones from them the acquired view should have 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/or 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 a razor blade using active vision is shown in Fig. 7. In first view (left column) no blade was detected, for this reason a new point of view is generated. In second view (middle column), a razor blade was detected, however, the estimated pose does not correspond to a “good view”. Thus, a new view (right column) was obtained to corroborate the detection. We can see the ability of our approach to find the target object looking for good views even with partial occlusions.

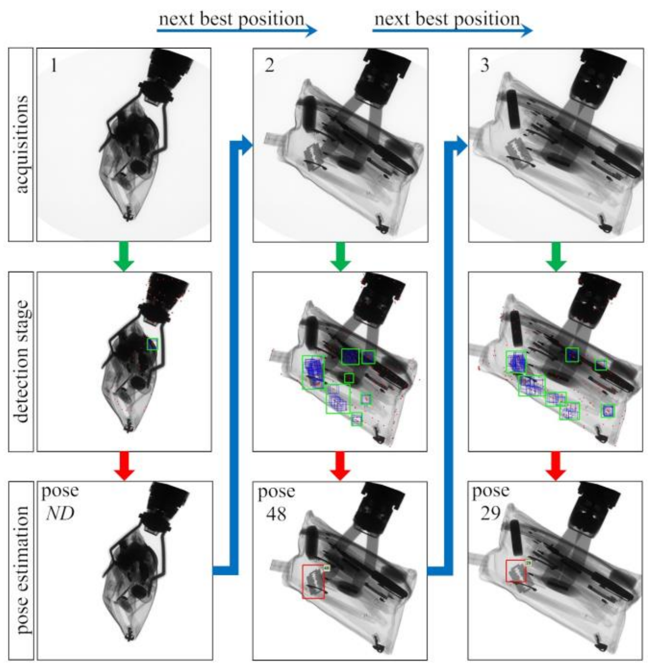


Figure 7: Detection of a razor blade in pencil case using active vision.

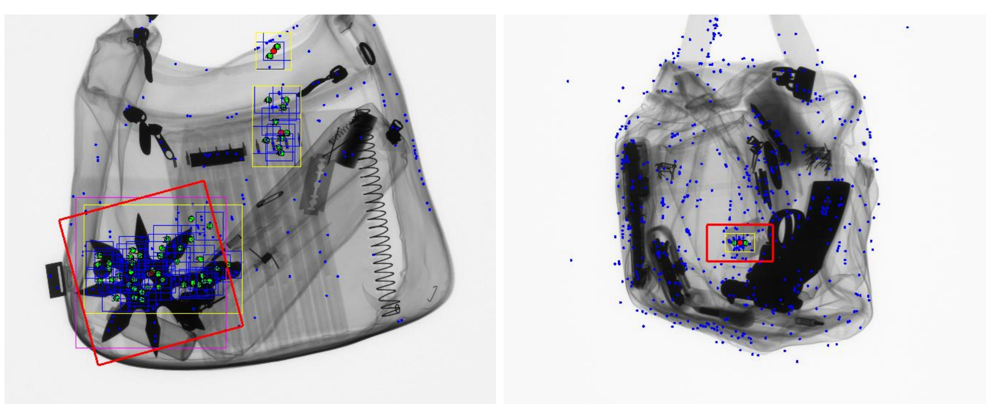


Figure 8: Detection of a shuriken (left) and a razor blade (right) using our approach based on ISM in a single view (see red parallelogram).

We evaluated two approaches that are able to detect the target object in a single view: *i*) SIFT matching detects regions of the image which SIFT descriptors are similar to SIFT descriptors of reference objects [16]; and *ii*) Implicit Shape Model (ISM) [14] 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. Fig. 8 shows the detection of a *shuriken* (commonly known as ninja star) and a razor blade using ISM.

Using a robotic arm and a semi-automatic manipulator system, the robustness and reliability of the method have been verified in the automated detection of razor blades located inside of nine different objects showing promising preliminary results: in 130 experiments we were able to detect 115 times the razor blade with 10 false alarms, achieving recall of 89% and precision of 92%.

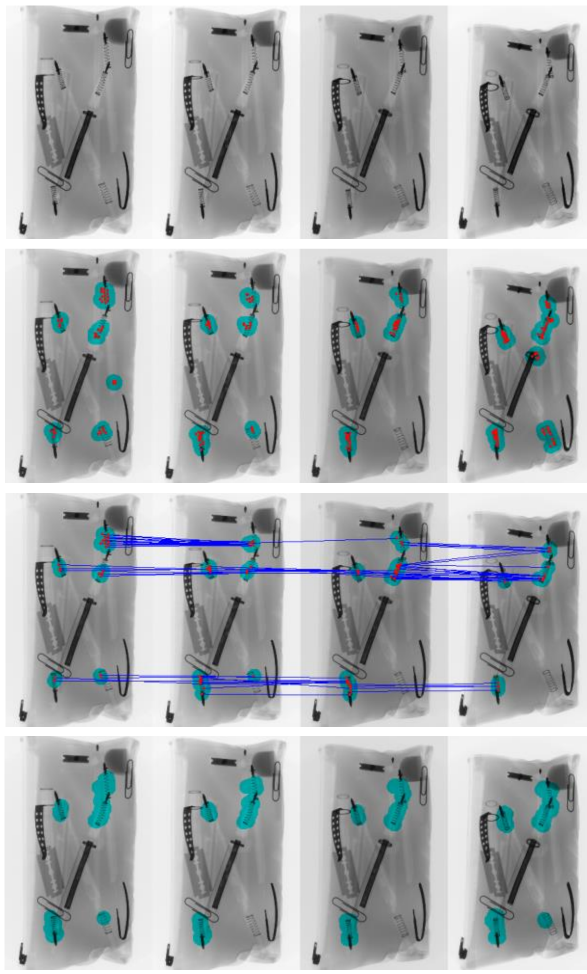
The reader is referred to [36] for a detailed description of the active vision algorithm and more examples.

3.3 Recognition using an efficient search algorithm

Recently, we developed a new method based on multiple X-ray views to recognize certain regular objects with highly defined shapes and sizes. The method 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:** We learn a classifier h to recognize patches or keypoints of the parts that we are attempting to detect. Images are 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 keypoints per image are detected, and for each keypoint a descriptor $\mathbf{y}$ is extracted using, for example, LBP, SIFT and SURF, among others [29]. In this supervised approach, each descriptor $\mathbf{y}$ is 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 is designed which maps $\mathbf{y}_t$ to their classification label c_t, thus, $h(\mathbf{y}_t)$ should be c_t. In monocular testing images (see for example Fig. 9a) keypoints are extracted and classified using h. Classified keypoints are clustered using Mean Shift algorithm [7]. Only those clusters that have a large enough number of keypoints are selected. They will be called *detected monocular keypoints* as illustrated in Fig. 9b.
- **Multiple view analysis:** Multiple view analysis performs the recognition of objects of interest in three steps: *i*) Data association: In this step, we find matchings for all detected monocular keypoints in all consecutive images of the sequence. For each detected monocular keypoint, we efficiently seek in a dense grid of points the potential matching candidates using a lookup table that is computed off-line [27] as shown in Fig. 9c. *ii*) 3D analysis: From each pair of matched keypoints, a 3D point is reconstructed. Similarly to the monocular detection approach, neighbor 3D points are clustered in the 3D space using

Mean Shift algorithm [7], and only those clusters that have a large enough number of 3D points are selected. *iii*) 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 keypoints 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 keypoints individually classified as *c*', and this number represents a majority in the cluster (see Fig. 9d).



a

b

c

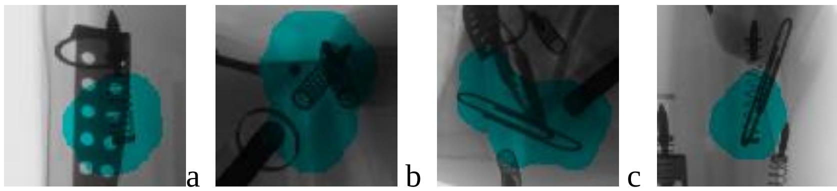
d

Figure 9: Multiple view detection of springs in a pencase: a) original test sequence, b) detected monocular keypoints, c) matched keypoints, and d) detection.

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 we are trying to recognize is occluded by a part of another class. In this case, there will be keypoints in the cluster assigned to both classes; however, we expect that the majority of keypoints will be assigned to the true class if there are a small number of keypoints misclassified. Results with some overlap, where the task was the recognition of springs and clips, are illustrated in Fig 10.

In order to illustrate the effectiveness of the proposed method, experimental results on recognizing regular objects –clips, springs and razor blades– in pen cases are shown achieving around 93% accuracy for 120 objects.

The reader is referred to [27] for a detailed description of the active vision algorithm and more examples.



a b c d

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

4 Conclusions

In our paper, we would like to make a contribution to object recognition in baggage screening. We have based our methods on potent ideas such as: *i*) *detection windows*, as they obtain a high performance in recognition and detection problems in computer vision; *ii*) *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; *iii*) *efficient visual search*, given the speeds involved when searching for objects; and *iv*) *active vision* that is able to adequate the viewpoint of the target object in order to obtain better X-ray images to analyze.

We believe that it would be possible to design an automated aid in a target detection task using the proposed algorithms. We have shown that these preliminary results are promising. However, since the performance of the methods has been verified on a few radioscopic image sequences, an evaluation on a broader data base is necessary.

Acknowledgments

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References

[1] B. Abidi, Y. Zheng, A. Gribok, and M. Abidi. Improving weapon detection in single energy x-ray images through pseudocoloring. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 36(6):784 –796, nov. 2006.

[2] O. Abusaeeda, J. Evans, D. D., and J. Chan. View synthesis of KDEX imagery for 3D security X-ray imaging. In *Proc. 4th International Conference on Imaging for Crime Detection and Prevention (ICDP-2011)*, 2011.

[3] M. Bas¸tan, W. Byeon, and T. M. Breuel. Object Recognition in Multi-View Dual X-ray Images. In *British Machine Vision Conference BMVC*, 2013.

[4] M. Bas¸tan, M. R. Yousefi, and T. M. Breuel. Visual words on baggage Xray images. In *Computer Analysis of Images and Patterns*, pages 360–368. Springer, 2011.

[5] J. Chan, P. Evans, and X. Wang. Enhanced color coding scheme for kinetic depth effect X-ray (KDEX) imaging. In *Security Technology (ICCST), 2010 IEEE International Carnahan Conference on*, pages 155–160, oct. 2010.

[6] Z. Chen, Y. Zheng, B. R. Abidi, D. L. Page, and M. A. Abidi. A combinational approach to the fusion, de-noising and enhancement of dual-energy x-ray luggage images. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2005.

[7] D. Comaniciu and P. Meer. Mean shift: A robust approach toward feature space analysis. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24(5):603–619, 2002.

[8] J. Ding, Y. Li, X. Xu, and L. Wang. X-ray image segmentation by attribute relational graph matching. In *8th IEEE International Conference on Signal Processing*, volume 2, 2006.

[9] P. Dollár, C. Wojek, B. Schiele, and P. Perona. Pedestrian detection: An evaluation of the state of the art. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(4):743–761, 2011.

[10] T. Franzel, U. Schmidt, and S. Roth. Object detection in multi-view X-ray images. *Pattern Recognition*, pages 144–154, 2012.

[11] R. Gonzalez and R. Woods. *Digital Image Processing*. Pearson, Prentice Hall, third edition, 2008.

[12] R. I. Hartley and A. Zisserman. *Multiple view geometry in computer vision*. Cambridge University Press, second edition, 2003.

[13] G. Heitz and G. Chechik. Object separation in X-ray image sets. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR-2010)*, pages 2093–2100, 2010.

[14] B. Leibe, A. Leonardis, and B. Schiele. Robust object detection with interleaved categorization and segmentation. *International Journal of Computer Vision*, 77:259–289, 2008.

[15] D. Liu and Z. Wang. A united classification system of X-ray image based on fuzzy rule and neural networks. In *Intelligent System and Knowledge Engineering, 2008. ISKE 2008. 3rd International Conference on*, volume 1, pages 717 –722, nov. 2008.

[16] D. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110, 2004.

[17] Q. Lu and R. Conners. Using image processing methods to improve the explosive detection accuracy. *IEEE Transactions on Applications and Reviews*, Part C: Systems, Man, and Cybernetics, 36(6):750–760, 2006.

[18] M. Mansoor and R. Rajashankari. Detection of concealed weapons in Xray images using fuzzy K-NN. *International Journal of Computer Science, Engineering and Information Technology*, 2(2), 2012.

[19] J. Matas, O. Chum, M. Urban, and T. Pajdla. Robust wide-baseline stereo from maximally stable extremal regions. *Image and Vision Computing*, 22(10):761–767, 2004.

[20] D. Mery. Crossing line profile: a new approach to detecting defects in aluminium castings. In *Scandinavian Conference on Image Analysis (SCIA)*, volume 2749, pages 725–732, 2003.

[21] D. Mery. Explicit geometric model of a radioscopic imaging system. *NDT & E International*, 36(8):587–599, 2003.

[22] D. Mery. Automated detection in complex objects using a tracking algorithm in multiple X-ray views. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 41–48, 2011.

[23] D. Mery. X-Ray Testing by Computer Vision. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 360–367, 2013.

[24] D. Mery and D. Filbert. Automated flaw detection in aluminum castings based on the tracking of potential defects in a radioscopic image sequence. *IEEE Transactions on Robotics and Automation*, 18(6):890–901, December 2002.

[25] D. Mery and V. Riffo. Automated Object Recognition in Baggage Screening Using Multiple X-ray Views. In *52nd Annual Conference of the British Institute for Non-Destructive Testing*, Telford, Sept. 2013.

[26] D. Mery, V. Riffo, G. Mondragon, and I. Zuccar. Detection of regular objects in baggages using multiple X-ray views. *Insight*, 55(1):16–21, 2013.

[27] D. Mery, V. Riffo, I. Zuccar, and C. Pieringer. Automated X-Ray Object Recognition Using an Efficient Search Algorithm in Multiple Views. In *IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pages 368–374, 2013.

[28] S. Michel, S. Koller, J. de Ruiter, R. Moerland, M. Hogervorst, and A. Schwaninger. Computer-based training increases efficiency in X-Ray image interpretation by aviation security screeners. In *Security Technology, 2007 41st Annual IEEE International Carnahan Conference on*, pages 201–206, Oct. 2007.

[29] K. Mikolajczyk and C. Schmid. A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(10):1615–1630, 2005.

[30] E. Murphy. A rising war on terrorists. *Spectrum, IEEE*, 26(11): 33–36, nov 1989.

[31] N. Murray and K. Riordan. Evaluation of automatic explosive detection systems. In *Security Technology, 1995. Proceedings. Institute of Electrical and Electronics Engineers 29th Annual 1995 International Carnahan Conference on*, pages 175 –179, oct 1995.

[32] S. Nercessian, K. Panetta, and S. Agaian. Automatic detection of potential threat objects in X-ray luggage scan images. In *Technologies for Homeland Security, 2008 IEEE Conference on*, pages 504 –509, may 2008.

[33] A. Noble, R. Gupta, J. Mundy, A. Schmitz, and R. Hartley. High precision X-ray stereo for automated 3D CAD-based inspection. *IEEE Trans. Robotics and Automation*, 14(2):292–302, 1998.

[34] C. Oertel and P. Bock. Identification of objects-of-interest in X-Ray images. In *Applied Imagery and Pattern Recognition Workshop, 2006. AIPR 2006. 35th IEEE*, page 17, oct. 2006.

[35] S. M. Rahman, M. O. Ahmad, and M. Swamy. Contrast-based fusion of noisy images using discrete wavelet transform. *Image Processing, IET*, 4(5):374–384, 2010.

[36] V. Riffo and D. Mery. Active X-ray testing of complex objects. *Insight*, 54(1):28–35, 2012.

[37] L. Schmidt-Hackenberg, M. R. Yousefi, and T. M. Breuel. Visual cortex inspired features for object detection in X-ray images. In *Pattern Recognition (ICPR), 2012 21st International Conference on*, pages 2573–2576. IEEE, 2012.

[38] M. Singh and S. Singh. Optimizing image enhancement for screening luggage at airports. In *Computational Intelligence for Homeland Security and Personal Safety, 2005. CIHSPS 2005. Proceedings of the 2005 IEEE International Conference on*, pages 131 –136, 31 2005-april 1 2005.

[39] H. Strecker. Automatic detection of explosives in airline baggage using elastic X-ray scatter. In *Medicamundi*, volume 42, pages 30–33, jul. 1998.

[40] A. Torralba, R. Fergus, and W. Freeman. 80 million tiny images: A large data set for nonparametric object and scene recognition. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 30(11):1958–1970, 2008.

[41] B. Triggs, P. McLauchlan, R. Hartley, and A. Fitzgibbon. Bundle adjustment: a modern synthesis. *Vision algorithms: theory and practice*, pages 153–177, 2000.

[42] D. Turcsany, A. Mouton, and T. P. Breckon. Improving feature-based object recognition for X-ray baggage security screening using primed visualwords. In *IEEE International Conference on Industrial Technology (ICIT)*, pages 1140–1145, 2013.

[43] P. Viola and M. Jones. Robust real-time object detection. *International Journal of Computer Vision*, 57(2):137–154, 2004.

[44] C. von Bastian, A. Schwaninger, and S. Michel. *Do Multi-view X-ray Systems Improve X-ray Image Interpretation in Airport Security Screening?*, volume 52. GRIN Verlag, 2010.

[45] A.Wales, T. Halbherr, and A. Schwaninger. Using speed measures to predict performance in X-ray luggage screening tasks. In *Security Technology, 2009. 43rd Annual 2009 International Carnahan Conference on*, pages 212 –215, oct. 2009.

[46] G. Zentai. X-ray imaging for homeland security. *IEEE International Workshop on Imaging Systems and Techniques (IST)*, 2008.