1. Dmytro MAMCHUR[1,2], 2. Janis PEKSA[3], 3. Soledad Le CLAINCHE[4], 4. Ricardo VINUESA[5]

[1]Turiba University, Graudu Street 68, LV-1058 Riga, Latvia
[2]Kremenchuk Mykhailo Ostrohradskyi National University, Pershotravneva 20, 39600, Kremenchuk, Ukraine
[3]Institute of Information Technology, Riga Technical University, Kalku Street 1, LV-1658 Riga, Latvia
[4]School of Aerospace Engineering, Universidad Politécnica de Madrid, 28040 Madrid, Spain
[5]FLOW, Engineering Mechanics, KTH Royal Institute of Technology, SE-100 44, Stockholm, Sweden
ORCID: 1. 0000-0002-2851-878X; 2. 0000-0003-4125-494X; 3. 0000-0003-3605-7351 4. 0000-0001-6570-5499

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Analysis of the state of the art on non-intrusive object-screening techniques

***Abstract**. The paper is devoted to an analysis of the modern methods and techniques used for non-intrusive object screening. First, currently used technology and the principle of equipment operation are described. Next, the ways for improving the reliability and efficiency of the screening process and ways for its automation are indicated. Finally, a schematic of an automated screening system that uses additional sensors and implements AI-based analysis for automatic detection and distinguishing between legal, illegal and illicit items inside the object under inspection is proposed.*

***Streszczenie.** Artykuł poświecony jest analizie nowoczesnych metod i technik stosowanych w nieinwazyjnej detekcji obiektu. Omówione zostały obecnie używane metody detekcji, a następnie wskazano na możliwości poprawy efektywności i wiarygodności tych metod poprzez wprowadzenie automatyzacji procesów automatyzacji. W końcu pokazano schemat systemu automatycznej inspekcji, w którym wykorzystano dodatkowe czujniki oraz elementy sztucznej inteligencji, pozwalające na rozróżnianie legalnych i nielegalnych rzeczy w obiekcie poddanemu inspekcji. (**Prezentacja* **state of the art** ***w technice nieinwazyjnej inspekcji obiektu**).*

Keywords: X-ray machine, odour analysis, spectroscopy, artificial intelligence, deep learning, image recognition
Słowa kluczowe: aparat rentgenowski, analiza zapachu, sztuczna inteligencja, uczenie głębokie, rozpoznawanie obrazów

Introduction

The question of developing novel approaches and techniques for non-intrusive object inspection aimed at advanced detection of illegal, dangerous, and illicit items in cargo, post mail, parcels, personal belongings are essential nowadays due to, on the one hand, increased postal and trading flow caused by rapid e-trading development amplified with COVID-19 quarantine restrictions [1–4], and on the other hand, increased refugees flow-thru external EU borders [5–6]. These increased flows could be used by unscrupulous citizens as well as by organized crime groups to deliver dangerous or illicit items, such as weapons, explosives, powders, drugs, smugglings, undeclared cash, due to the low quality of object screening, especially during rush hours on the control points.

Thus, there is a necessity to develop novel non-intrusive approaches to a screening process, which will provide the possibility to automatically control huge object flows with increased screening speed, causing the least possible intrusion into customer's privacy, along with a low rate of false threat detection and high accuracy of threat and illicit items detection results.

Currently, one of the most popular non-intrusive screening techniques employed for this task is X-ray screening [7–10]. This technique is successfully implemented on different control points to inspect small, medium, and large size objects. However, at the first stages of their era, X-ray machines provided black-and-white images for the screened object's content, and trained operators should recognize illegal items based on their experience.

With the development of screening and processing techniques and the growth in number of objects needed to be inspected, advanced techniques were required to increase screening efficiency. Therefore, the first attempts implied training screeners with digital simulators (X-ray tutors) [7–10].

Further advanced in computer processing powers, and the rise of novel approaches to employing the computer vision for solving human-related tasks involved using deep learning, machine learning, and neural networks techniques to image processing and recognition [11–17]. These techniques proved to be efficient, but they also have downsides, as they are not always able to recognize materials of which item is made of, and illegal items could be hidden with the change of their typical shape.

On the other hand X-ray image recognition techniques aimed to recognize abnormalities in the images. They are trained using datasets for "normal" and "abnormal" packages, which could make them possible to detect abnormalities related to possible threats [18].

Along with this, recent research suggests that existing types and methods for X-ray image processing, even if they could be improved with the implementation of novel AI-based techniques, could not satisfy current needs in required inspection speed and result accuracy [19].

Thus, additional techniques, methods, and equipment should be used to improve the quality of assessment. In addition to item shape recognition, most of these techniques aimed to reveal the structural composition of the objects under inspection, as malefactors often change the shape of the dangerous object [19, 20].

Among possible solutions, it is suggested to implement different novel types of sensors able to extract additional information from the X-ray screening process or analyse additional parameters of the items inside the inspected object, such as odour composition analysis or spectroscopy.

X-ray inspection principles

One of the most widespread methods for non-intrusive inspection is X-ray inspection. This type of inspection has proved to be reliable during past decades. At first, it allowed an X-ray image for the inspector with the screening window, then with the computer monitor, which allowed the inspector to view the internal content of the inspected object without its opening. Finally, based on acquired experience, the trained inspector could recognize the typical threat of illicit items from their shape on the X-ray image.

With the latest advances in artificial intelligence (AI) technologies, it constantly grows several attempts to employ AI for X-ray image recognition tasks, which could be in use for automatic detection of threat and illicit items presence inside the inspected object without its opening [12, 18, 21, 22].

We also should mention that there are different types of X-ray machines used for object inspection. The simplest ones allow receiving a 2D image of the inspected object in black-and-white colours, while advanced ones could provide even 3-D images of a screened object along with their contents, estimated type of material [19, 23, 24].

X-ray screening machines could provide single- or dual-energy analysis [23, 25, 26]. Single-energy machines generate images received from direct penetration of X-rays through an inspected object. Typically, it is a black-and-white image representing the "shadow" of an inspected object.

Dual-energy analysis machines are based on the Compton effect, allowing one to single out two types of X-ray energies: high and low. When the X-ray quantum collides with a particle of material, its energy is transferred to an electron. An excited electron dumps the energy received from quantum in an X-ray photon of lower energy. Thus, in the case of the radiation scattering by substances with a small atomic number, practically, all scattered radiation has a shifted wavelength. Thus, two energies appear in the X-ray spectrum: scattered low energy and initial high energy.

When the inspected object enters the tunnel and shades the photoelectric sensor, the signal from the sensor goes to the control unit, which starts the X-ray generator. As a result, X-ray radiation comes out from the collimator, penetrates thru the inspected object, and hits the detector.

In dual-energy machines, the number of detector modules is twice as large as in a one-energy system. Two sets of detectors with sensitivity to low and high-energy X-rays, respectively, are placed together to receive X-rays.

Depending on the signals received from both detectors, the image processing system can recognize the types of materials (mainly organic, inorganic, and mixtures) of the inspected object. The detector modules of the system are placed inside protected L-shaped panels and installed diagonally from the X-ray generator for scanning the entire section of the tunnel with X-ray.

Such construction excludes "blind" zones and allows one to inspect any part of an object passing through the tunnel.

Next, a highly efficient detector converts X-rays into a weak current signal, amplified and fed to Analogue-Digital Converter (ADC). Finally, these analog signals are converted into 16-bit digital signals, which are sent to a computer. The computer first corrects the discrepancy and offset of the digital signal from each pixel, then classifies organic and inorganic materials from the corrected low and high energy signals, and performs essential image processing functions, like image edge enhancement, correction of 16-bit low- and high-energy signals.

The signal of each graphical X-ray slice object turns to a line of an image on the display screen.

The grey level indicates the degree of absorption of X-ray radiation in the inspected object.

Since the object is transported along the tunnel by a conveyor at a constant speed, the system scans it as a series of X-ray graphic slices. The processed X-ray images of the object are sequentially reflected on a computer screen.

All X-ray graphic slices of the inspected object images are combined and form a complete X-ray image.

The typical schematic structure of an X-ray machine is presented in Fig. 1.

To help the inspector understand the details of the image and draw the correct conclusion. In addition, the system provides them with several functions for analyzing and evaluating the image.

Applying these functions does not change the image data itself. Disabling these functions restores the original image.

Campton effect allows one to determine the adequate atomic number (Z_{eff}) of a material. Based on this parameter, it is possible to distinguish the type of material. Also, X-ray screening software allows one to assign a different colour to a different type of material (table 1).

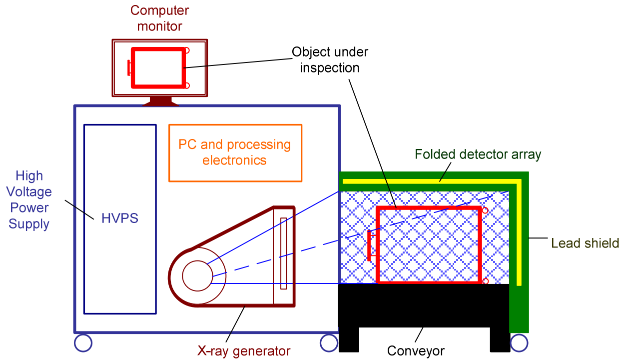

Fig.1 Typical schematic structure of X-ray machine

Table 1. An example of pseudo colour assignment depending on the material type under X-ray machines inspection

Category	Z_{eff}	Colour	Typical material
Organics	< 10		Compounds of a light element such as hydrogen, carbon, nitrogen, and oxygen, including the majority of explosives (such as nitroglycerine), plastics (such as polypropylene), paper, cloth, food, wood, and water
Mixture materials	10..18		Medium mass metal elements (e.g., aluminum) and salts
Non-organic	> 18		Heavy metals (e.g., titanium, chromium, silver, nickel, iron, copper, zinc, and lead).

Identification material by its atomic number helps detect explosives, drugs, and other dangerous or illicit items. For example, Z_{eff} for water and plastic explosives equals 7, mixed drugs or explosives equals 8, and pure narcotic substances equal 9.

Thus, the combination of shape-recognition techniques with material atomic number analysis automatically identifies dangerous and illicit goods inside the inspected object with no need to open it in most cases using modern X-ray machines.

However, such powerful machines are typically quite expensive, and their software, along with AI training techniques and other threat-detection process details, are typically unavailable for the public, and they differ depending on the manufacturer. So, nowadays, all details related to used techniques and threat detection methods are dispersed by different X-ray machine manufacturers.

There were attempts to unify threat-detection techniques based on X-ray images analysis and make it independent of the type of machine manufacturer and its software. Thus, in

[27], it was analyzed that more than 38 thousand X-ray scans were gained from different types of X-ray machines. For example, (HCVS and CAB200 from Smithsdetection and laboratory setups from partner universities) investigated more than one thousand objects from different views and angles, aiming to create a database containing common patterns for different legal, illegal or illegal or illicit items independently on the X-ray machine type. Based on this investigation, in Ref. [28] it was proposed to analyze X-ray images received from different types of X-ray machines, train AI to recognize legitimate and illegal goods, and combine all this knowledge in a centralized reference database, which should be available online and assist cargo inspectors from different countries in their operations. However, after the project duration time is expired, there is no freely available information about the created reference database that could be used to assist during cargo or other object-inspection procedures.

In Ref. [29] it is pointed out that late advances in AI technologies for threat detections based on their shape recognition techniques are highly reliable and allow one to successfully detect shapes with performance comparable to humans deploying convolutional neural networks. On the other hand, automation for semantic analysis of scanned objects, aimed to reveal illegal, dangerous or high-value goods, which could not be present in the watch list of illicit items, is still the subject for more profound attention. Also, still unsolved for automatized X-ray inspection is the detection of deviations from expected (Anomaly Detection, AD) which could indicate concealment or subterfuge.

In [29], it was described as an approach to the solution of the AD problem, based solely on X-ray images analysis. However, this approach also implies a necessity to train AI for AD recognition, which, in sequence, should imply the use of a reference database to compare inspected items with during real-life detection.

In order to improve readability of X-ray images it may be used modal decomposition techniques aimed to reconstruct 3D field from 2D data or 2D fields from 1D data [30–33]. In combination with machine learning tools, these techniques could be used to develop predictive models fully data-driven that could be applied to data classification and prediction basing on X-ray images [34].

Thus, it is concluded that nowadays techniques for automatic threat detection during non-intrusive object inspection are actively developing. Industrial security systems manufacturers currently use several highly efficient techniques, but they are unavailable for mass use. On the other hand, there are attempts to develop inspection-aid systems, which implies cloud databases including a broad number of detected threats and illicit goods patterns, which could be used by different inspection organizations independently on the type of X-ray screening equipment.

However, such systems are trained only using visual and partially structural object recognition approaches, which do not always provide reliable results, especially during illegal object detection.

Thus, it is necessary to employ additional techniques when there are doubts regarding the legitimacy of inspected objects to inspect as accurately, fast, reliable, and non-intrusive as possible.

Further analysis allowed us to single out the following techniques which could be exploited to solve this task.

Material chemical composition analysis

X-ray screening is successfully implemented for shape recognition and, in some cases, for material recognition based on its density and effective atomic number determination. However, in some cases, it could be harder to distinguish dangerous items from legal ones based on X-ray image analysis only, and a deeper inspection could be needed. As the second stage of inspection, the sniffer dogs or other sensitive animals could be in use. These techniques aimed to exploit bio-organisms, such as pets, insects, and others, to detect certain phenomena, materials, objects (such as drugs and explosives). However, these methods, even if they are proved to be highly effective, are relatively slow. Also, it should be mentioned that sniffing dogs or other animals or insects typically could perform their duty for about one hour, and they need to be rested [19]. With the late advances in microelectronics and computer techniques, attempts have arisen to deploy novel sensors to substitute bio-organisms in solving these tasks. Thus, analysis on the principle of dog's or rat's odour recognition enabled developing sensors able to analyze odour and detect the possibility of containing a certain amount of drugs or explosives traces in the nearby air [35–37]. In [38], a comprehensive review was published on the implementation of bioelectronic noses to odour recognition. Researches have shown the possibility of detecting explosive substances. For example, trinitrotoluene, cyclotrimethylenetrinitramine, pentaerythritol tetranitrate. Based on the relative concentration (or vapor pressure) of these substances in the air.

Currently, odour-sensing technology could single out into two big groups: ones that use technical sensors and ones which use biosensors. Technical sensors are made of only technical components. Therefore, they could be divided into two big groups: electronic noses (technical systems consisting of various chemical sensors converting chemical information into an analytic signal) and sensors implementing instrumental analytics (mass gas chromatography, ion mobility spectrometry). Indifference to a technical sensor, biosensors include integrated biological elements to sense the odour. Natural elements (bioreceptors) typically could be used cells, proteins, cell tissue, or nanovesicles [36]. When a substance to be measured contacts a bioreceptor, it ignites a biochemical reaction that could be measured and recorded and then analyzed.

Based on analogy with smell sense, the typical process of odour recognition could be presented as follows (fig. 2). In the first stage, an odor sample should be collected using either a technical or biosensor. The second stage is processing the odour sample, recognizing different patterns based on trained AI (typically, CNN's). The third stage is the determination of odour patterns and their classification, aiming to single out target patterns (drugs, explosives). The final stage is alarming in case of dangerous or illegal item detection.

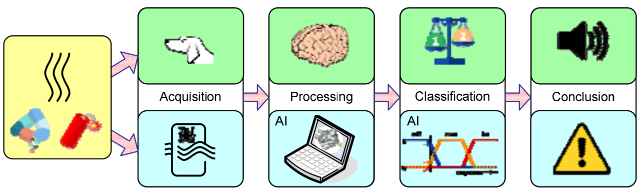

Fig. 2 Typical process of odour recognition

Of course, the presence in the air of specific chemical components does not always mean that illegal or dangerous items are inside the inspected object. To reliably detect the presence of such items, an AI-based convolutional-neural-network (CNN) approach is currently under deep research.

Material analysis techniques

Another possible solution for improving the quality of non-intrusive object screening is using different spectroscopy methods to detect the type of material objects is made; however, these methods typically implement

In [39], it was proposed to use ultrasonic sensors to detect media types inside some tanks. It was successfully tested on several types of explosive liquids and proved to be a reliable one.

In [40], authors, using the profound ultraviolet photoacoustic spectroscopy principle, experimentally detected such explosives as pentaerythritol (PETN), 2,4,6-trinitrotoluene (TNT), and ammonium nitrate (AN) with 1second accumulations within 3 meters distance.

In [41], the possibility of distinguishing pharmaceutical materials through packaging was demonstrated using spatially offset Raman spectroscopy within seconds. In addition, the proposed device could be portable or mobile.

So, spectroscopy-based techniques could additionally be employed to distinguish the type of item material both for explosives or drugs detection during non-intrusive object inspection.

Proposed structure of automated threat detection system

Based on the provided analysis, it was shown that there is currently a necessity to develop an automated non-intrusive threat detection system, which could provide improved performance compared to existing ones with a faster processing speed and a lower false-detection with the increased unerring detection rate.

The primary inspection should be done based on X-ray images derived from existing X-ray machines, as the most common practice in the non-intrusive inspection process. However, the developed system should be independent of the type of the used X-ray machine to make it possible to use the system despite the machine manufacturer and software. Thus, it should operate with the previously prepared pure X-ray images in a determined file format for further processing.

To develop a reference database, which contains comprehensive information on legitimate and illegal goods patterns. AI techniques should be employed, and CNN's should be trained to recognize these patterns independently on the X-ray machine type.

All acquired data, including trained ANN's, patterns for legitimate and illegal items, should be included in a knowledge base available online for permitted users. Based on this knowledge base, it should be generated a reference database containing a portion of information suitable for a particular inspection point depending on the typical object flow through this point. In case of an unclear situation, there should be the possibility of accessing a broad knowledge base using cloud technologies to make them more precise inspection or insert novel, previously unknown data into this knowledge base.

During normal exploitation, there should be the possibility for continuous training and populating knowledge base with novel data. It should be realized by the inspector who uses the system, and, after verification, novel cases for pattern recognition are inserted into the knowledge base.

In case when there is uncertainty in detection results based on X-ray image analysis, additional automatic inspection should be done based on the use of additional sensors for chemical and material analysis. The idea of implementing additional sensors is to maximize automatic inspection, minimizing human factors in false positive or false negative detection results.

Based on described assumptions, it was developed schematic representation of the proposed system shown in fig. 3. In this system the first block is used for data acquisition from X-ray and other sensors when needed. The Data Processing block exploited the local reference database with the most typical patterns suitable for specific inspection points. If there is uncertainty in the decision based on X-ray image analysis, the system requests to employ an additional sensor. Depending on the suspicion type, a specific type of necessary sensors and control should be chosen and returned to the Data Acquisition block.

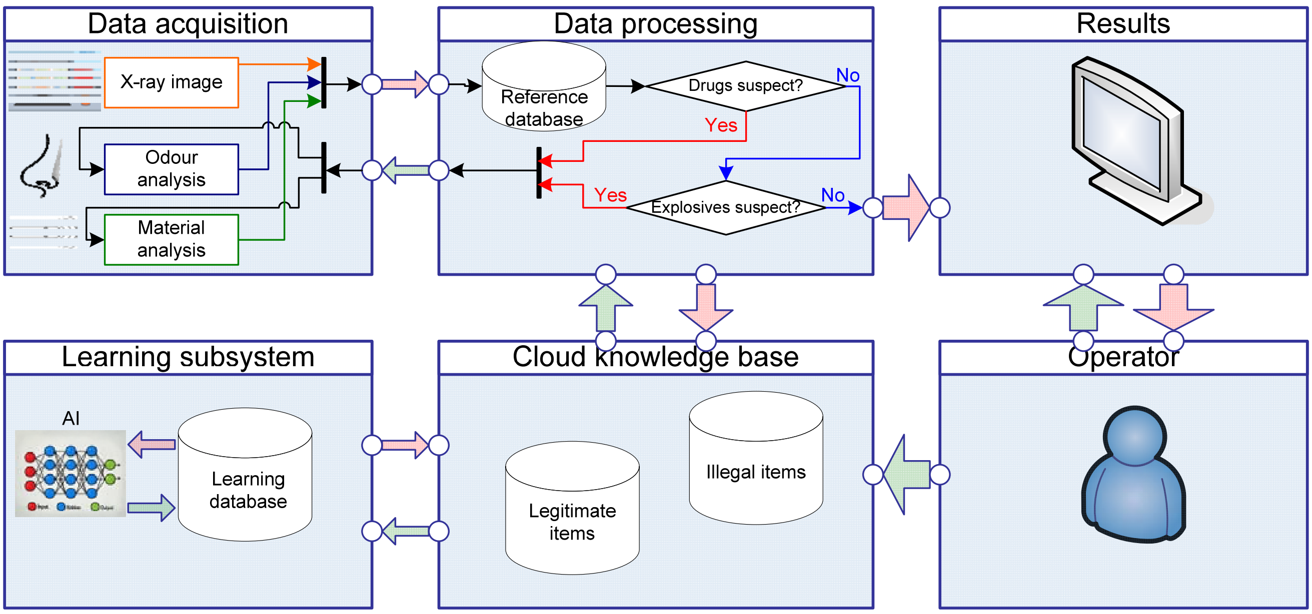

Fig 3. Schematic representation of the proposed system

Conclusions

In this work, the current state of the art on non-intrusive object inspection techniques was described. Furthermore, the most promising non-intrusive screening techniques, including single- and dual-energy X-ray images analysis, odour analysis, spectroscopy for material analysis, etc., were described.

Based on the provided analysis, we conclude that current techniques and equipment do not always satisfy screening needs within increased object flows on control points, especially during rush hours. One of the solutions for this problem is to implement a multi-sensor system, which will provide additional analysis on suspected items when there are doubts in decision processes relying only on X-ray image analysis.

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***Authors**: assoc. prof. Dmytro Mamchur, Turiba University, Graudu Street 68, LV-1058 Riga, Latvia, Kremenchuk Mykhailo Ostrohradskyi National University, Pershotravneva 20, 39600, Kremenchuk, Ukraine, E-mail: dgmamchur@gmail.com; Ph.D. candidate Janis Peksa, Institute of Information Technology, Riga Technical University, Kalku Street 1, LV-1658 Riga, Latvia, E-mail: janis.peksa@rtu.lv; assoc. prof. Soledad Le Clainche, School of Aerospace Engineering, Universidad Politécnica de Madrid, 28040 Madrid, Spain, E-mail: soledad.leclainche@upm.es; assoc. prof. Ricardo Vinuesa, FLOW, Engineering Mechanics, KTH Royal Institute of Technology, SE-100 44, Stockholm, Sweden, E-mail: rvinuesa@mech.kth.se.*

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