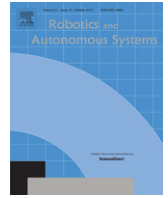




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## Robotics and Autonomous Systems

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## Visual classification of waste material for nuclear decommissioning

Affan Shaukat<sup>a,\*</sup>, Yang Gao<sup>a</sup>, Jeffrey A. Kuo<sup>b</sup>, Bob A. Bowen<sup>c</sup>, Paul E. Mort<sup>d</sup><sup>a</sup> Surrey Space Centre, Faculty of Engineering and Physical Sciences, University of Surrey, GU2 7XH Guildford, UK<sup>b</sup> National Nuclear Laboratory, Chadwick House, Warrington Road, Birchwood Park, Warrington, WA3 6AE, UK<sup>c</sup> National Nuclear Laboratory, Havelock Road, Derwent Howe, Workington, Cumbria, CA14 3YQ, UK<sup>d</sup> Sellafield Ltd, Sellafield, Seascale, Cumbria, CA20 1PG, UK

## HIGHLIGHTS

- Waste from decommissioned nuclear plants are required to be sorted and segregated.
- A vision system for autonomous classification of nuclear waste is proposed.
- The lowest possible passive vision sensors are used due to operational constraints.
- Proposed system is tested using dataset generated from nonradioactive simulants.
- Results are presented using performance metrics with conclusions and future work.

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## ABSTRACT

Redundant and nonoperational buildings at nuclear sites go through the process of 'decommissioning', involving decontamination of nuclear waste material and demolition of physical infrastructure. One challenging problem currently faced by the nuclear industry during this process is the segregation of redundant waste material into a choice of 'post-processes' based upon the nature and extent of its radioactivity that may pose a serious threat to the environment. Following an initial inspection, waste materials are subjected to treatment, disruption and consigned to various types of export containers. To date, the process of objects (waste) classification is performed manually. In order to automate this process, robotic platforms can be deployed that utilise robust and fast vision systems for visual classification of nuclear waste material. This paper proposes a novel solution incorporating a machine vision system for autonomous identification of waste material from decommissioned nuclear plants. Rotation and scale invariant moments are used to describe object shapes in the visual scene whereas a *random forest* learning algorithm performs object classification. Using nuclear waste simulants (from the nuclear plant decommissioning process), an exhaustive 'proof-of-concept' quantitative assessment of the proposed technique is performed, in order to test its applicability within the current problem domain.

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The nuclear industry maintains an important share of the total global electricity production around the world. Ever since the first nuclear power plant got commissioned in 1954 (*Obninsk*, former Soviet Union), there has been a continual rise in the number of new plants around the globe. On average, a growth rate of about 7 reactors per annum (1954–1974) and 2–3 reactors per annum (1970s–mid-2000). The period between mid-2000s and the beginning of 2011 witnessed an accelerating growth rate [1] also known as the "nuclear renaissance". At present, there are over 210 nuclear

power plants in Europe accounting for nearly one-third of the total electricity generation in the EU and is forecasted to increase over the next decade [2]. While the number of new reactors grow, many of the old ones are reaching or have already reached the end of their working lives and therefore require *decommissioning*. While some countries are putting efforts to extend the life of their older nuclear power plants, others, such as the UK, are investing into building and improving facilities for decommissioning their redundant plants [2].

Decommissioning of nuclear plants involves dismantling and removing the facilities [4]. Some of these steps may involve dismantling the whole or part of the plant infrastructure, followed by decontamination of building material and components. The process of *decommissioning* produces multiple categories of solid

\* Corresponding author.

E-mail address: [a.shaukat@surrey.ac.uk](mailto:a.shaukat@surrey.ac.uk) (A. Shaukat).URL: <http://www.surrey.ac.uk/ssc/research/star-lab/> (A. Shaukat).<http://dx.doi.org/10.1016/j.robot.2015.09.005>

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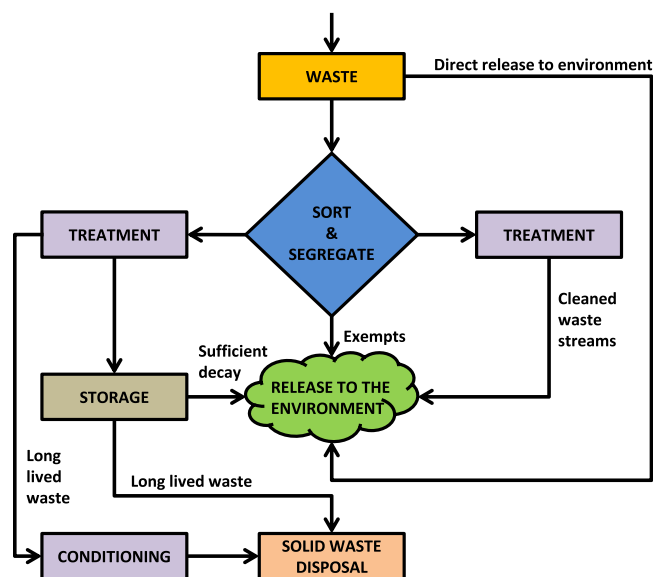


Fig. 1. Flow sheet for redundant nuclear waste disposal and storage options [3].



Fig. 2. Typical solid waste material produced from nuclear plant decommissioning process (National Nuclear Laboratory and Sellafield Ltd, UK).

waste material; usually hardware components and building material with long lived activation products e.g., gloves, metal, glass, hand tools, sludges from effluent treatment plants and isotope cartridges [3]. The process of *decontamination* usually produces liquid waste, such as, chemical solutions and contaminated oils. It is imperative that all resulting waste materials are disposed safely to protect the workforce, public and the environment.

Nuclear waste disposal and storage involve a number of important processes. An initial task of characterising the waste material is performed using the radiological, physical-chemical characteristics and origin of the waste material, more formally '*sorting*', followed by physical separation for post processing, more formally '*segregating*' [3]. The two terms are used interchangeably or more often together as the '*sort-and-segregate*' process. Fig. 1 illustrates an overview of the processes involved in the management of nuclear waste generated from the decommissioning process. The sort-and-segregate step is fundamental to decommissioning. To date, the segregation of different types of solid waste material is performed using teleoperated robotic arms, which reduces operator dosage. Fig. 2 shows a sample of the solid waste material. This process is time consuming. One means of reducing the time scales for this characterisation process is to equip the robots with intelligent machine vision systems that can perform part or whole classification using visual characteristics such as *object shape*.

Machine vision can provide a safe, and nondestructive method for the autonomous characterisation of scene objects as an important source of initial inspection before using any means of tactile knowledge retrieval method. The aim of this paper is thus to find an appropriate mechanism for visually identifying a collection of objects representing real-world nuclear plant components and evalu-

ate its potential for application to the problem of autonomous sorting and segregation of nuclear waste material.

The remaining part of the paper is structured as follows: Section 1 provides brief literature on machine vision systems and their industrial applications, more importantly the protection of critical system components within the nuclear industry. Section 2 introduces the proposed vision system for automated classification of solid nuclear waste. Section 3 provides an overview of the experimental objectives defined for the current research work. Section 4 describes the experimental dataset and nuclear waste simulants used for the current work. Section 5 presents experimental results followed by a short discussion about the system performance in Section 6. Finally the conclusions drawn from the experimental results are discussed in Section 7 including ideas for future developments and novelties.

## 1. Background

### 1.1. An overview of machine vision systems

Machine vision systems are considered to be one of the most important methods of environmental perception for autonomous platforms. They are capable of providing important information about objects in the visual scene such as size, colour, shape and textures etc. A typical machine vision system comprises multiple hardware and software components. The nature of perceived visual information depends upon the type of imaging sensor used. While imaging objects in the visible (VIS) colour region tends to dominate a majority of the applications [5–9], the use of invisible light spectrum such as ultraviolet (UV), near-infrared (NIR), and infrared (IR) has niche applications [10–13]. The following discussion will be restricted to vision systems utilising the VIS spectrum since they are versatile sensors providing contextually rich information compared to other invisible sources [14]. As such invisible light sensors and their applications are beyond the scope of the current work.

Standard VIS spectrum cameras convert three-dimensional environments into a 2-D image representation with high degree of spatial and grey-scale resolution including colour information. Additional depth information can be made available either via dedicated *active-range-sensors*, or software methods such as, stereopsis, shape-from-shading and structure-from-motion. The two-dimensional image is rectified, i.e., corrected for distortions or anomalies by using either the *camera calibration* information or the *fundamental matrix* [15]. Additional filters are applied to the rectified images for image denoising e.g., *median*, *mode*, and *mean* [16]. This is usually followed by image segmentation, feature detection/extraction and classification.

The process of visual object detection can be more generally described as verifying the presence or absence of a particular object within the input stimulus or image [17]. Depending upon the types of features used by the detection *search* strategy, object detection techniques can either be classified as '*edge-based*' or '*patch-based*' [18]. Edge-based methods identify discontinuities or point changes, such as, variation in intensity, orientation, illumination etc., and are represented as object boundaries or shape contours [19]. Patch-based methods use local appearance cues as image characteristics, such as, '*corner detection*', '*SIFT*' and '*SURF*' [5].

Classification identifies the class membership of an observation, that is, the input feature space, based on some training dataset comprising instances with known class labels using a supervised learning algorithm. The choice of using a specific type of feature set or a learning algorithm depends upon system design requirements, environmental constraints, sensory information and computational resources [17]. Object '*shape*' is considered to be one of the

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