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Multi-Sensor Identification Of Unmarked Piece Goods

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Abstract

The seamless fusion of the virtual world of information with the real physical world of things is considered the key for mastering the increasing complexity of production networks in the context of Industry 4.0. This fusion, widely referred to as the Internet of Things (IoT), is primarily enabled through the use of automatic identification (Auto-ID) technologies as an interface between the two worlds. Existing Auto-ID technologies almost exclusively rely on artificial features or identifiers that are attached to an object for the sole purpose of identification. In fact, using artificial features for the purpose of identification causes additional efforts and is not even always applicable. This paper, therefore, follows an approach of using multiple natural object features defined by the technical product information from computer-aided design (CAD) models for direct identification. By extending optical instance-level 3D-Object recognition by means of additional non-optical sensors, a multi-sensor automatic identification system (AIS) is realised, capable of identifying unpackaged piece goods without the need for artificial identifiers. While the implementation of a prototype confirms the feasibility of the approach, first experiments show improved accuracy and distinctiveness in identification compared to optical instance-level 3D-Object recognition. This paper aims to introduce the concept of multi-sensor identification and to present the prototype multi-sensor AIS.

Keywords

3D-Object recognition; Automatic identification; Computer-aided design (CAD); Direct identification; Multi-sensor identification; Natural identifiers

1. Introduction

Digitalisation and Industry 4.0 are far-reaching fields of action with great relevance for society, education and economy in all areas of life worldwide. The core of the ideas behind Industry 4.0 results from research and development activities in engineering or natural sciences which are closely linked to information and communication technology as well as automation technology [1]. One promising concept behind Industry 4.0 is the seamless integration of the real world of things with the virtual world of information, widely referred to as the 'Internet of Things' (IoT) [2]. Tracing back the origins of this term, it can be found that it was already coined around the year 2000 by the founders of the original Massachusetts Institute of Technology (MIT) Auto-ID Center, which is nowadays part of the Auto-ID Labs research network [3]. The latter institutions conducted research on automatic identification (Auto-ID) technologies for industry aiming to establish the foundation for the IoT [2], and they identified Auto-ID technologies as an important technology for the future advancement of the IoT and therefore Industry 4.0.

2. Motivation

In the context of industry, the term ‘automatic identification technology’ refers to a variety of techniques for the purpose of logistical goods identification within material flow systems, aiming to synchronise the information flow with the material flow by collecting identity information [4, 5]. Besides less known techniques, visual code identification (approx. 70%) and radio-frequency identification (RFID) dominate today’s applications [5]. Common to both techniques is the use of artificial features for the purpose of identification. Visual codes are applied to objects either by labelling (e.g., thermal transfer labels, etc.) or by direct marking (e.g., laser engraving, printing, etc.) [5-7]. For identification using RFID, active or passive electronic transponders are attached to objects, which are available in various designs (e.g., adhesive labels, press-in cartridges, etc.). Active RFID transponders differ from passive ones by an integrated power supply in form of a battery [7].

It is obvious that the utilisation of the above-mentioned artificial identifiers requires additional process steps for their attachment to objects. If an object itself is to bear such an artificial identification feature, its geometry must also be appropriate in size and shape, which must already be considered in its design phase and offers difficulties in application if the geometry cannot be adapted as is the case with functional surfaces for example. When going through different production steps, it may be necessary to remove previously applied artificial identifiers and afterwards reapply them to objects as they would be destroyed (e.g., painting, thermal treatment, etc.), also offering drawbacks in application. Active RFID transponders furthermore require maintenance in case their batteries have to be replaced. In conclusion, the use of artificial identifiers generates costly additional efforts and is not always applicable.

Identification based on features that characterise objects by nature is referred to as ‘direct identification’ in the literature [5-8]. Natural identification features of objects are mass properties, geometry, surface structure/texture, colour/appearance and material [5-10]. Using these features instead of artificial identifiers eliminates the issues discussed in the previous paragraph.

Modern machine vision (MV) systems can recognise three-dimensional objects from image data based on their appearance or geometry, known as ‘3D-Object recognition’ [11]. As a basis for the recognition, computer-aided design (CAD) models can be used, which serve to define known objects within a knowledge base [12]. However, these MV systems are only capable of interpreting visually perceptible characteristics, which limits their suitability for direct identification as they cannot distinguish based on the remaining natural identification features. As a consequence, the distinctiveness and accuracy of identification using 3D-Object recognition are limited, which also limits possible application tasks.

In industry, CAD models are widely used as virtual product models containing related product information [13]. In particular, the technical information, as a subset of the product information, provide details on the natural characteristics that can be used for identification purposes mentioned above [14]. CAD models are thus an ideal source for direct identification, defining industrial objects throughout the entire life cycle following the paradigm of product data management (PDM).

This leads to the core idea behind multi-sensor identification, which consists of extending the perceptual capacity of MV systems for 3D-Object recognition by using further sensors to detect the natural identifiers not considered so far. The resulting multi-sensor automatic identification system (AIS) is thus no longer dependent on the use of artificial identification features, while at the same time offering higher potential use for identification tasks than MV systems.

3. State of the art

This section briefly summarises the state of the art in related fields and provides insight into the theoretical foundations of multi-sensor identification.

3.1 Existing approaches for direct identification

While there are many approaches or technologies for indirect identification by means of artificial identification features, there are only a few approaches for direct identification by exploiting the natural features of objects, often referred to as 'fingerprints' [9].

Laser surface authentication (LSA) takes advantage of naturally and randomly occurring imperfections on the surfaces of objects to be identified. These imperfections cause diffuse scattering when exposed to a focused laser beam. This diffuse scattering, also known as laser granulation or laser speckle, captured by photodetectors arranged at different angles generates a pattern of the reflected intensity unique to the object. Applying statistical methods, a binary descriptor can be generated from this intensity pattern, which can then be used for identification similar to a human fingerprint [9, 15].

The characterization of grinding imprints by means of their roughness profile offers another possibility for direct identification. Due to the grain structure of grinding wheels and the wear occurring during grinding processes, random grinding patterns are created on the surfaces of workpieces. After recording such a ground surface with a high-resolution camera, descriptors can be generated by means of various algorithms. These descriptors can be used for identification and are also robust to perturbations like corrosion [10].

3.2 Instance level 3D-Object recognition based on CAD models.

The recognition of three-dimensional objects from image data is commonly referred to as '3D-Object recognition'. In the literature, a basic distinction is made in terms of the level of recognition and the type of input image data used. Instance level recognition describes the identification of distinct object instances [11]. In contrast to category-level recognition, this means that an object to be recognized can be explicitly assigned to a known object within the recognition knowledge base. For the generation of this recognition knowledge base, which describes the objects known to the recognition system, CAD models can be used [12]. Numerous feature descriptors are available for both 2D and 3D image data. Due to the fact that the depth information in 3D image data provides higher quality, 3D feature descriptors are preferably used for recognition based on CAD models [11, 12, 16]. Most modern 3D feature descriptors encode surface normal information, that is obtained from point clouds [16, 17]. The development of such descriptors has been stimulated by the increasing availability and affordability of 3D sensors, that directly capture point clouds of objects.

CAD models primarily describe the geometric shape of objects and appear in three different basic forms of representation: wireframe models, surface models and solid models [18]. By means of virtual rendering or sampling methods, these representations can be transformed into point clouds.

For describing complete point clouds of objects or CAD models, global descriptors are particularly suitable. One very accurate and performant global descriptor is the clustered viewpoint feature histogram (CVFH) descriptor [16]. Global descriptors are the basis of global processing pipelines for 3D-Object recognition. The basic global recognition pipeline consists of the steps 'description' and 'matching', optionally six degrees of freedom (6DoF) pose estimation can be performed. In a preceding offline process, descriptors are generated for all point clouds of CAD models and saved as a recognition knowledgebase. The actual recognition takes place in an online process, which commences with describing the sensor point cloud of an object to be identified in order to generate a so-called scene descriptor. The latter is then matched against all descriptors of known objects within the recognition knowledgebase, where the quality of each match is assessed by means of a distance metric. If there is a sufficient degree of agreement between the scene and the knowledge base descriptors, an object is recognised. By performing the 6DoF pose estimation step, the three-dimensional geometric transformation that transfers the CAD point cloud to the sensor point cloud can be determined [19].

3.3 Technical information within product models

Product models in the industry comprise defining information for products. One subcategory of this product information is technical information, typically originating from product development. In particular, the geometrical and technological information within the technical information contain details regarding the physical features of products or objects [14].

CAD models are product models which are used in particular to store and distribute technical information [18]. There are many different data formats for CAD models, which differ greatly regarding their information content. Typically, CAD models contain the following technical information: geometries, mass properties, material properties. Some CAD models can serve as a basis for photorealistic rendering, which generates detailed information on their appearance or texture.

4. Concept for multi-sensor AIS

This section presents the generic process for identification based on natural identification features, a software processing chain based on it as well as a hardware concept for a multi-sensor AIS.

4.1 Generic process of identification

In the literature, there are only a few formulations regarding the process of identification (e.g. [20]). These formulations mainly focus on the superficial phases that are passed through to identify an object in a practical environment while neglecting the process of identification itself. For this reason, the formulation of a generic process of identification is necessary.

Identification essentially consists of the assignment of identification features of an object to be identified to the identification features of a known object to retrieve associated identity information. The fundamental prerequisite for performing an identification is, therefore, an identification knowledge base (e.g., register of citizens) that defines individual identities by linking identification features (e.g., appearance from passport photo, height, eye colour, etc.) with identity information (e.g., name, address, etc.). Identity is therefore only valid within the framework of an identification knowledge base and can have different levels of uniqueness. The level of uniqueness of identity depends on the uniqueness of the identification features used. If several objects possess identical identification features (e.g., article number), they share the same identity (e.g., master data record) within the scope of the identification knowledge base. The identification features must therefore always be chosen with regard to the desired identification task and the required level of uniqueness.

An identification knowledge base K consists of j pairs $\left(S_{F_j}, S_{I_j}\right)$ which define identities (see Equation 1). S_F and S_I describe sets of identification features and identity information with arbitrary length (see Equation 2 and Equation 3).

$$K = \left\{\left(S_{F_1}, S_{I_1}\right)_1, \left(S_{F_2}, S_{I_2}\right)_2, \dots, \left(S_{F_j}, S_{I_j}\right)_j\right\} \quad (1)$$

$$S_F = \{F_1, F_2, \dots, F_k\} \quad (2)$$

$$S_I = \{I_1, I_2, \dots, I_l\} \quad (3)$$

The actual process of identification now describes the search for the pair (S_F, S_I) within K, where S_F matches the feature set S_f of an object to be identified (see Equation 4).

$$S_f = \{f_1, f_2, \dots, f_m\} \quad (4)$$

The above formulation of the generic process of identification is the basis for the multi-sensor identification procedure as several features are evaluated. This is not the case with state-of-the-art identification systems that rely on only one identification feature (e.g., label with identification number). In addition to the uniqueness of each individual identifier, a higher degree of uniqueness is created through the way several identification features are combined.

4.2 Processing chain for multi-sensor AIS based on CAD-Models.

The processing chain consists of an offline and an online process. The offline process generates the identification knowledge base from the CAD models, while the online process performs the actual identification.

4.2.1 Offline process for identification knowledge base generation

The inputs for the offline process (see Figure 1) are the CAD models of objects to be identified. For each CAD model, a descriptor for 3D-Object recognition is created after transformation into a point cloud. Together with the identity information (identification number and description), as well as the information on weight, colour/appearance and centre of mass location, these descriptors are stored in the identification knowledge base. The identification knowledge base is the result of the offline process and is subsequently provided to the online process.

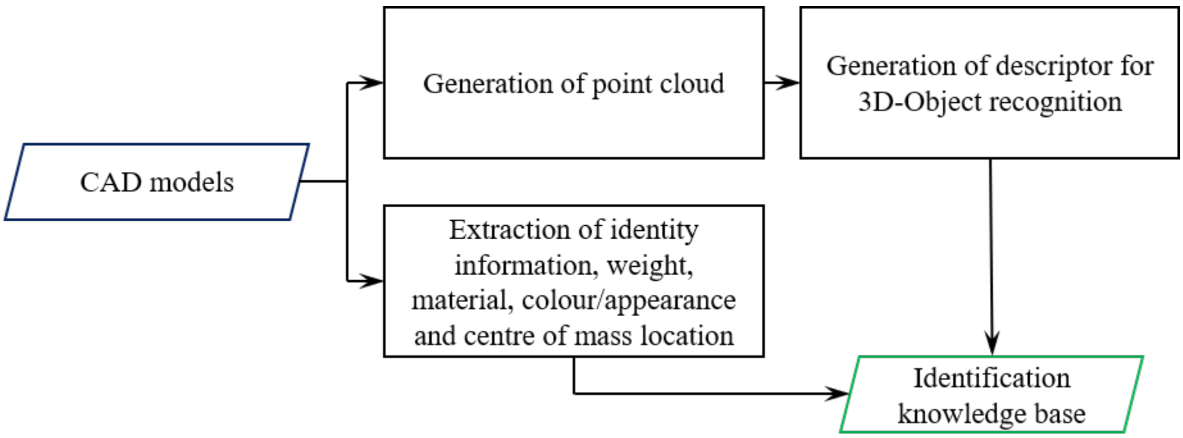

Figure 1: Offline process for identification knowledge base generation from CAD models; input (blue) output (green)

4.2.2 Online process for multi-sensor identification

The inputs for the online process (see Figure 2) are sensor inputs acquired from a scene containing an object to be identified as well as the identification knowledge base from the offline process. The inputs “Sensor point cloud” and “Sensor colour/appearance” can be obtained from 3D-Scanners. Regarding the inputs “Sensor weight”, “Sensor material” and “Sensor centre of mass location” a sensor platform can be used which is presented at a later stage.

From the sensor point cloud, a descriptor for 3D-Object recognition is generated. Based on weight, material, and colour/appearance information the identification knowledgebase is prefiltered in order to only pass matching candidate objects to the “3D-Object recognition and 6DoF pose estimation” step. The descriptors of these candidate objects point clouds from the prefiltered identification knowledge base are then matched against the descriptor of the sensor point cloud in the sense of 3D-Object recognition. For the recognised object, an estimation of the 6DoF pose is carried out, which yields the geometric transformation in order to transform the CAD point cloud into the sensor point cloud. By means of this transformation, a "Centre of mass validation" step can be performed. This step serves to compare the centre of mass location from the CAD model with the centre of mass location detected by sensors, aiming to further improve the accuracy of identification. After successfully performing all steps of the online process, the identity information originating from the identification knowledge base are available.

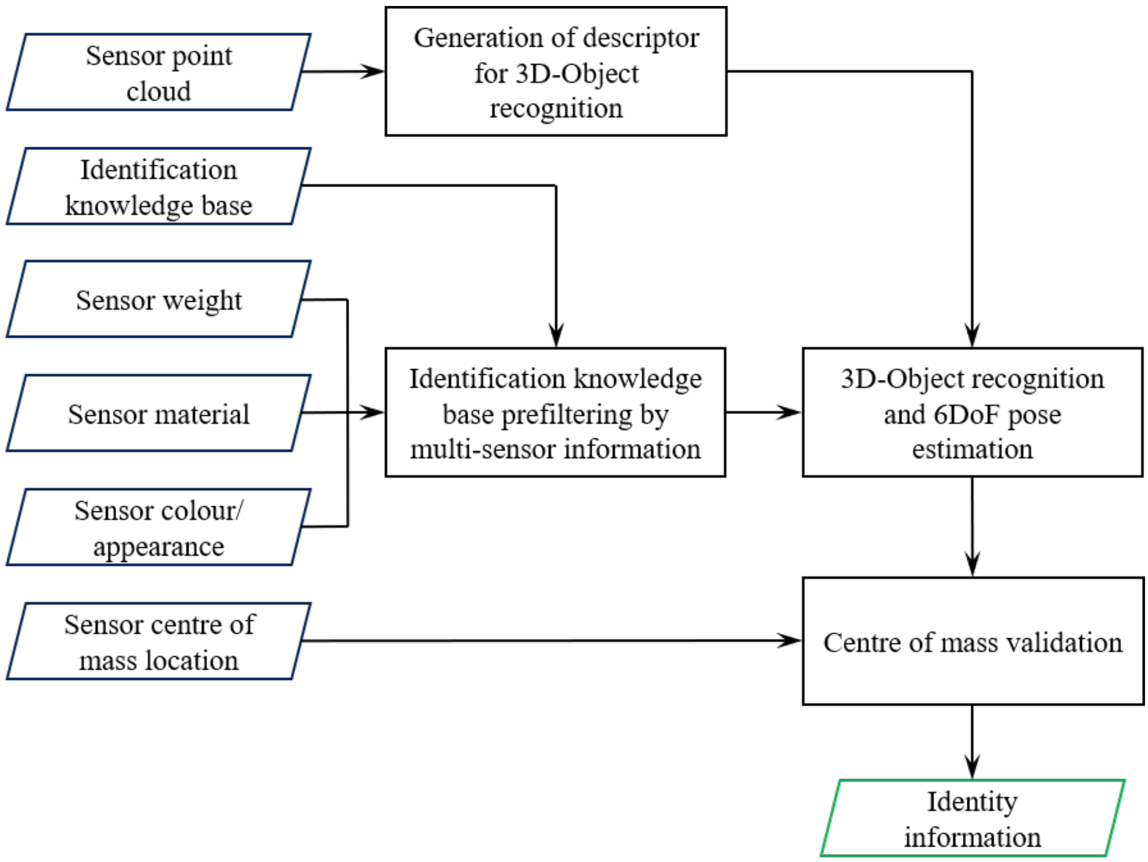

Figure 2: Online process for multi-sensor identification; inputs (blue) outputs (green)

4.3 Hardware concept for multi-sensor identification

The concept for the acquisition of sensor inputs for the offline process consists of a structured-light 3D-Scanner in combination with a sensor platform (see Figure 3). The 3D-Scanner captures the point cloud and colour/appearance of the identification object, which is settled on the rotary device of the sensor platform. The rotary device rotates the object to be identified during scanning in order to obtain a complete scan. An inductive sensor is used to detect the object's material, which makes it possible to distinguish between metals and non-metals. Furthermore, the sensor platform consists of a weighing plate, which uses four force sensors to determine the weight and centre of mass location of the object.

As Figure 3 indicates, three coordinate systems occur in this arrangement: The coordinate system of the 3D-Scanner (indexed "S"), the coordinate system of the sensor platform (indexed "SP") and the coordinate system of the object (indexed "O"). These coordinate systems are important for the "Centre of mass validation" step of the online identification process as geometric transformations have to be applied in order to compare the centre of mass location between the CAD model and the physical identification object.

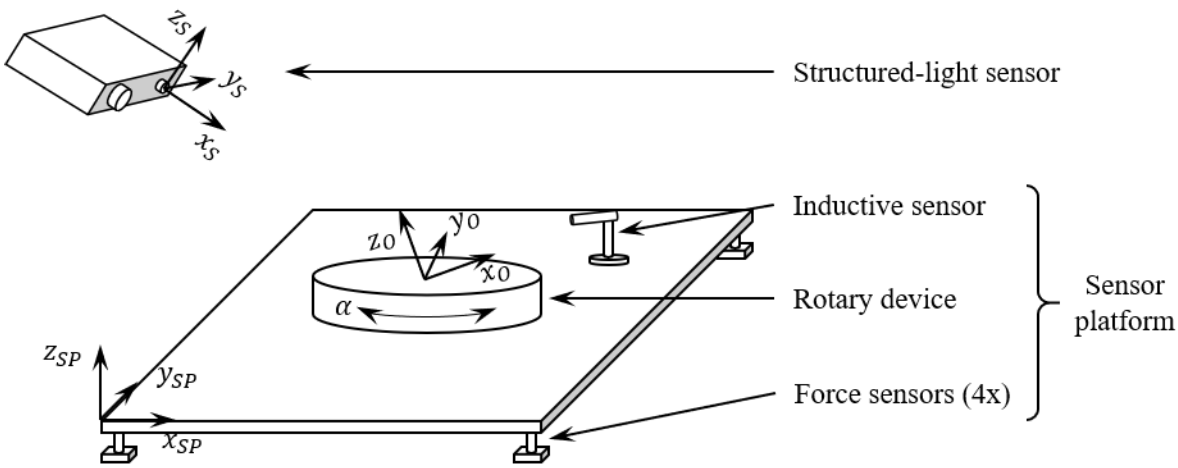

Figure 3: Sensor hardware concept for multi-sensor identification

5. Prototype implementation of multi-sensor AIS

Based on the above concept, the prototype for multi-sensor identification was implemented (see Figure 4). An ‘HP 3D Structured Light Scanner Pro S3’ in combination with an ‘HP Turntable Pro’ were used for the structure light sensor and the rotary device. The sensor platform is a custom implementation based on four load cells with HX711 amplifiers and an inductive proximity switch connected to an Arduino Nano. The weighing plate with the force sensors attached to it is made of steel so that a 3D-printed mount for the inductive proximity switch can be slid onto it by means of magnets.

Since 3D-Object recognition is computationally intensive, the above hardware was connected to a computer, serving as the main processing device. The software for the multi-sensor identification processing chain (see Section 4.2) was implemented using the programming languages Python and C++. In particular, the module performing 3D-Object recognition was implemented using the Point Cloud Library (PCL) written in C++ and then integrated into Python via the Pybind11 library.

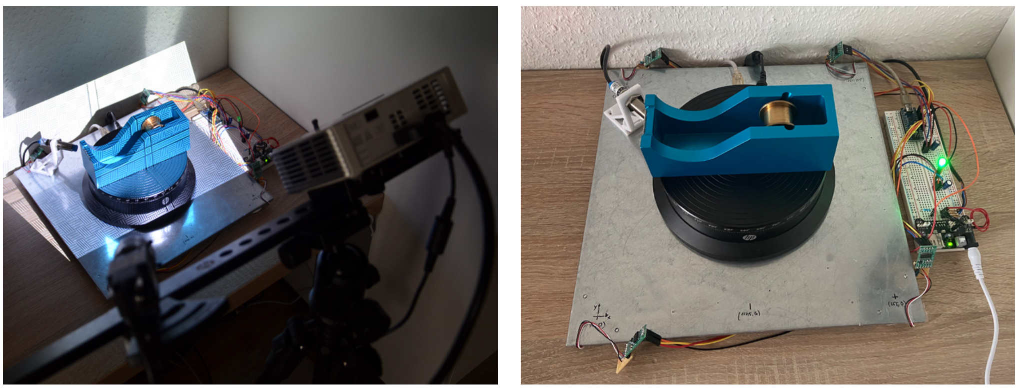

Figure 4: Prototype multi-sensor AIS with an identification object settled on the rotary device

6. Experimental verification of prototype multi-sensor AIS

For the experimental verification of the multi-sensor AIS, a set of 21 objects was compiled. Attention was paid to the fact that the objects vary in geometry, colour/appearance, weight, centre of mass location and material. From the set 16 objects were soda cans, differing in geometry (Ø67mm*115mm, Ø53mm*135mm, Ø67mm*115mm), colour/appearance (manufacturer specific design) and weight (full/empty). These soda cans were selected to be difficult to distinguish, as sometimes only one identifying feature differs from another object.

Using the prototype, 63 multi-sensor identifications were carried out, all of which were successful. The identification features were recorded reliably in all cases, leading to the appropriate identity information each time. On average, it took 3:08 minutes to identify one object by means of the online process. The main limiting factor here is the time needed for scanning, which is approximately 80% of the time span.

As a result of the investigation, it can be stated that the implemented prototype and algorithm for multi-sensor identification works well with the selected objects. The distinct identification of optically (geometry, colour/appearance) indistinguishable objects was always successful, which represents a clear advantage over conventional instance-level 3D-Object recognition systems in terms of accuracy and distinctiveness. There is still a lot of potential for more efficient software implementation and better hardware setup in order to drastically reduce the time needed for the identification process.

7. Summary and outlook

This paper introduces the concept of multi-sensor identification. Based on a newly introduced generic process of identification (see Section 4.1), a processing chain for multi-sensor identification using CAD models (see Section 4.2) is presented. A hardware concept for collecting multi-sensor information as inputs for the processing chain is described and implemented as the multi-sensor AIS prototype. Results of experimental verification proof the feasibility and effectiveness of multi-sensor identification.

Further research is needed in order to improve the hardware concept and the processing chain. The use of a robotic arm with integrated sensors in the gripper for collecting multi-sensor information and the manipulation of objects to be identified in front of a 3D-Scanner is worth investigating. Furthermore, the presented approach could be combined with the existing methods for direct identification (see Section 3.1) to utilize these distinct identification features. Here, CAD models would be useful for defining the location of 'fingerprints' (see Section 3.1) on objects. Since some types of 3D scanners already have integrated high-resolution cameras, using these identification features would not need any additional hardware.

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Biography

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