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AI-based vision system for collision detection in HRC applications

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Abstract

Human-Robot Collaboration (HRC) enabling mechanisms require real-time detection of potential collisions among human and robots. Taking under consideration the already existing standards and the literature, most of collision detection techniques require the integration of sensorial systems on the robot aiming to identify the contact events. This paper deals with a novel approach for the identification of human and robot collision based on vision systems. Moreover, Artificial Intelligent (AI) algorithms are required to classify the captured data near real-time and to provide a score about the collision status (contact or non-contact) between a human and the robot. Accordingly, the AI models should be trained using the appropriate image data enabling an accurate classification. The proposed system has been developed in a lab environment. A detailed presentation of the system implementation, its performance and the potential integration in a real industrial environment are discussed in this paper.

Keywords: Human-Robot collaboration; Artificial Intelligent; Vision system; Collision detection

1. Introduction

The increased utilization of robots in the modern industry introduces new types of manufacturing tasks which can be executed via robots. Although, in a number of cases, the human involvement is necessary for these tasks due to their dexterity. Industrial workplaces should be shared simultaneously among human and robots aiming to achieve the optimum level of productivity. Via HRC concept, the flexibility and versatility of the production is increased [1][2][3]. Human to robot cooperation concept applies in a number of industrial applications such as assembly tasks, packaging, welding tasks and object manipulation [4][5]. In modern cooperative tasks, robots and humans are working side by side in shared workspaces without the utilization of auxiliary safety devices such as steel fences or cages. In this way, operators can provide the human flexibility and perception while robots offer their strength and repeatability [6]. On the other hand, smart concepts which will allow the cooperation among the robots and the human in manufacturing tasks are needed. Human safety should always be ensured via advanced safety mechanisms.

Safety standards for the HRC concept have been defined from European Legislation. According the TS15066:2016, there are four modes which enable the safe cooperation among human and robots in common activities; the Safety Rated Monitored Stop (SMS), the Hand Guiding (HG), the Speed and Separation Monitoring (SSM) and the Power and Force Limiting (PFL). A number of methodologies for the deployment of the aforementioned modes have been developed by researchers. A number of them are analyzed in Section 2 of the paper. The selection of the appropriate mode depends on the industrial application and the mode's restriction.

The main scope of this paper is to introduce an enabling mechanism for HRC which can be easily deployed in any kind

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of robots. More specifically, they can be deployed in cases with small or large robots even if they are not categorized as cobots. The proposed mechanism utilizes vision systems and Artificial Intelligent algorithms to detect a collision among humans and robots. The key advantage of the proposed HRC enabling mechanism is its ability to detect a collision not only among the robotic structure and the humans but it also takes under consideration the robot’s tools such as grippers and other devices. More details of the proposed system are mentioned in the following sections.

This paper has been structured in five main sections. Section 1 makes a short introduction to the topic and the proposed system. Section 2 includes a detailed literature review indicating the current status of research while the identified gaps and the novelty of the proposed mechanism are presented. Section 3 describes the approach stating how the proposed system works. Finally, in Section 4, an initial case study in lab environment is presented while Section 5 states the conclusions and the future actions.

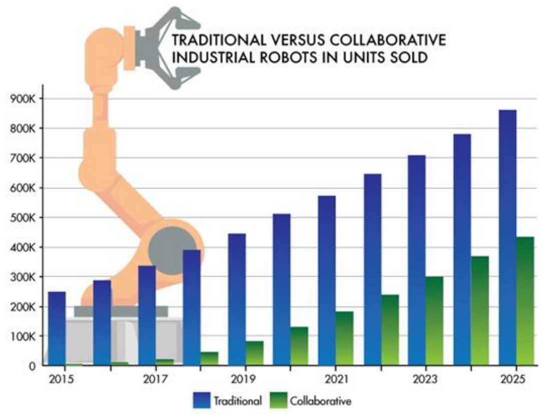

Fig. 1. Traditional versus Collaborative industrial robots in manufacturing [19]

2. Literature review & Gaps identification

Several approaches for collision prediction or detection have been developed in the literature while a number of products are available on the market. The majority of the discussed researches are based on neural networks or deep learning algorithms in combination with Industry 4.0 based sensors [7]. To achieve effective collaboration, awareness on the operational status is necessary. In [8], the proposed approach advances the literature in sensor data collection, integration and processing towards achieving context awareness on the shop floor. In [9], deep learning is utilized to classify, recognize and identify the context awareness for human-robot collaborated assembly tasks. Moreover, time-invariant dynamic models and supervised feedforward input-delay neural networks on signal processing has also been deployed to predict the robot behavior and foresee unexpected collision among the robots and humans [10]. In [11], a hazard identification technique coupled with a system description notation has been developed to identify potential hazards arising during collaboration tasks among humans and robots. Real time trajectory generation concept base on impact factors of a potential collision has also been investigated for HRC applications [12]. In [13], laser scanner and inertial measurement units have been utilized in dynamic shared workplaces with humans and obstacles. Other researches are focused on designing of the shared workplace aiming to enable the safe human-robot collaboration. In [14], a digital twin-based approach for designing and redesigning flexible assembly systems is presented. Synthesized data from multiple 2D–3D sensors are used to provide production data in a digital model and eventually, update the digital twin in runtime. Other HRC enabling mechanisms include a number of modules aiming to activate the robot perception. Manual guidance modules, contact sensors, vision systems and wearable devices including the augmented reality technology are some of the key technologies to enable the robot perception to work safely with human operators [15][16]. In the same direction, wearable devices such as Augmented Reality glasses and smartwatches have been used for closing the communication loop between operators and robots under a service-oriented architecture [17][18].

Regarding the already existing vision-based distance estimation solutions, the recent methods in vision-based technologies applied in human-robot interaction and/or collaboration scenarios have been analyzed in [24]. In [23], a novel methodology of real-time active collision avoidance in an augmented environment, where virtual 3D models of robots and real camera images of operators were used for monitoring and collision detection is presented. Advanced algorithms for cognitive vision, empowered by dynamic models of human walking, for detection and tracking of humans has also been investigated [21]. Another utilization of vision sensors is to establish safety spaces of arbitrary shape, size and position directly into the shared workspace of human and robot aiming to prevent from potential collisions [22].

Though several research efforts are reported, there are several limitations. One of the most challenging topics is that the current researches do not take into consideration the collision among robot tools and human. The reason is mainly due to the shape of the tools which in a number of cases consists of sharp parts. Accordingly, a very slight collision between a sharp tool and the human may cause a serious accident. Current researches based on force/torque monitoring are not able to track this type of collisions. Moreover, the existing systems focus on the identification of only one robot and humans using advanced sensory systems embedded in the robot. Eventually, the cost to utilize this concept in a production station with multiple robots is very high. Another limitation is that these sensors require advanced programming to be integrated on robots’ controller.

The proposed HRC enabling mechanism aims to deal with the aforementioned challenges using an AI-based vision system that is able to capture data from the working station and to identify the potential collisions near real time. This approach could also be applied for the whole robotic system including tools and other auxiliary devices integrated on the robot. The system will be able to identify the distances among the robot and the human in the 3D space using a vision system of three cameras able to cover all the required view ensuring the system performance. To achieve it, training datasets should be gathered for the AI model training. It is an easy to deployed system able to identify the collision among multiple robots and humans utilizing only one vision system and the AI model. To this end, a HRC enabling mechanism which detect potential collisions or situations which are relevant with warning about human safety is proposed. The current work aims to present this conceptual framework which has partially been validated in an experimental environment of a laboratory.

3. Approach

The proposed approach aims to provide a framework for the safe collaboration among humans and robots in a shared workspace. The proposed approach is illustrated in Fig. 2 while each module of the proposed HRC enabling framework is analyzed below.

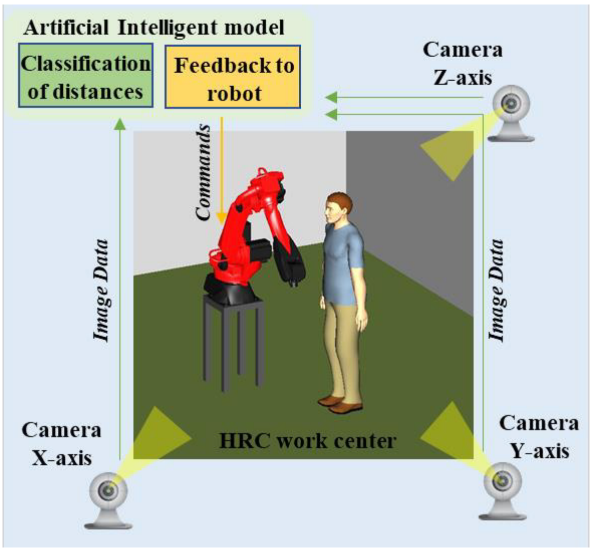

Fig. 2. Proposed HRC enabling framework

As far as the proposed system capabilities, it offers a full view of the workplace using a three-cameras vision system to ensure that the system will not fail to recognize any un-expected collision due to the camera's view. More specifically, one camera for each space dimension (X-axis, Y-axis and Z-axis) is considered. The image data of all cameras are analyzed to classify the distance among the robot and humans. The three cameras are part of a generic vision system able to provide the captured image data real time. The views of each camera for a specific pose of human and robot are depicted in Fig. 3. The system classifies all the image data and provide the results based on the worst scenario. A worst case scenario, it means the minimum distances which occur for one of the three dimensions in the space.

Moreover, the proposed HRC enabling mechanism is able to be deployed independently the human characteristics. More specifically, the AI-based model will be able to classify the distance between the robot and human independently the characteristics of the human who will be involved in the training data capturing phase. In most HRC enabling mechanisms, the safety standards depend on the potential human body regions which a collision may occur; there are different force limits for the head and different for the trunk.

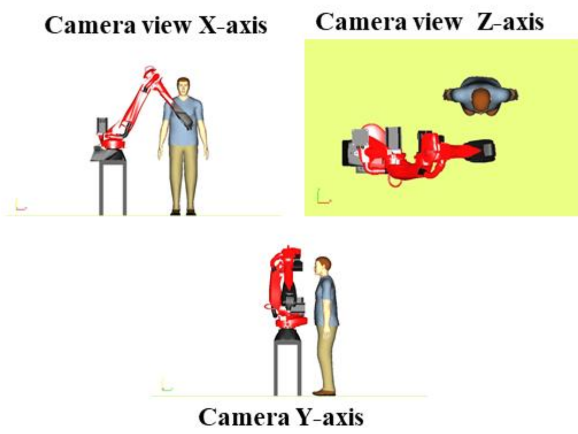

Fig. 3. Cameras views from the shared workspace

Due the core principles of the proposed system, there is not the need to identify the body area of a potential collision since it can be deployed as proactive system avoiding the collision when the distance between a human and the robot is very small. Fig. 4 depicts two indicative cases of potential collisions in different body regions.

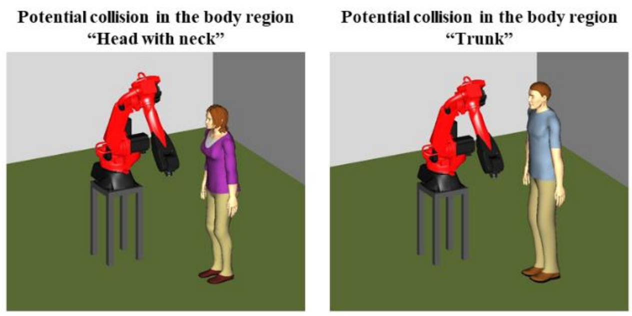

Fig. 4. Potential collisions in different body regions

Regarding the AI model which can be deployed for the proposed mechanism, it is based on Machine Learning techniques and mainly on the visual recognition. The implementation of a visual recognition application involves the utilization of Convolutional Neural Networks. According to Convolutional Neural Networks, there are three main phases to create and deploy a visual recognition application; the Training phase, the Classification phase and (optionally) the Retraining phase to improve the system performance.

The training phase is the first one and very vital for the success deployment of a visual recognition application. In this phase, image datasets are captured and categorized in classes based on common characteristics. In this work, the main characteristic of for this categorization is the distance. Then, the different classes are labelled by a user. Since multiple classes are required for the training phase, the corresponding image data should be gathered. The procedure involves the existence of a human and a robot in a shared workplace. To ensure the human safety, the robot is static while the human will move around the robot and the cameras capture the data from the three space dimensions. Then, the robot should be moved in another configuration and human to repeat the same procedure. Each class requires at least 10 images while a

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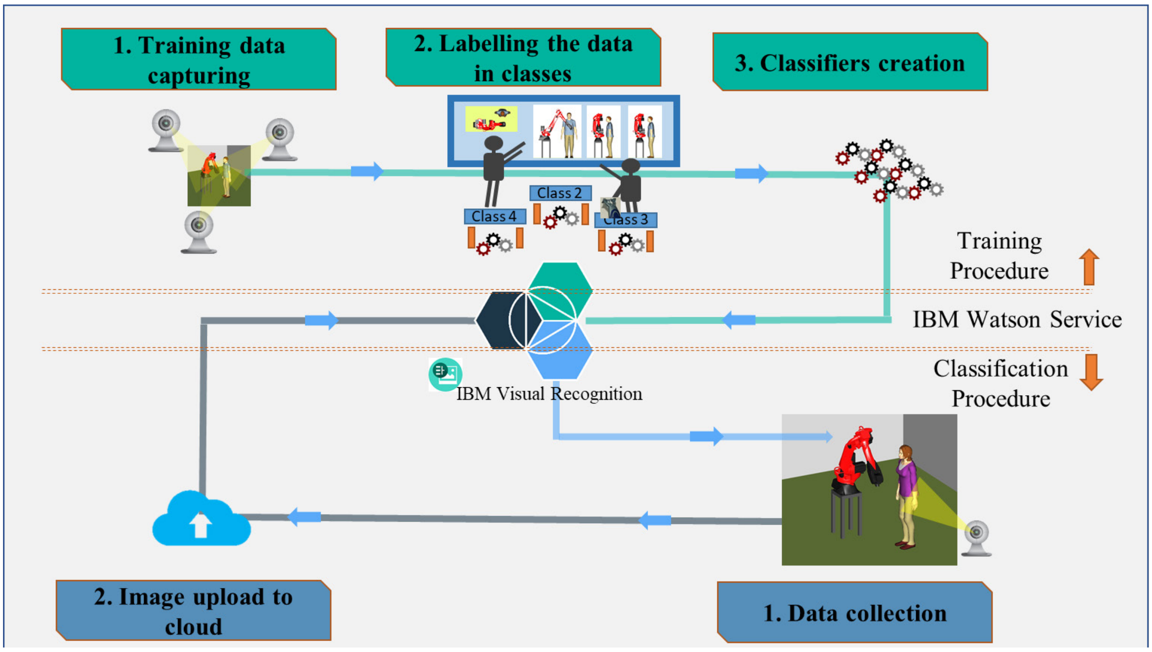

Fig. 5. System approach

representative label based on the distance between human and robot should be defined. Potential changes on the workspaces, such as motion of other humans or machines, should be taken under consideration during the collection of the training datasets. The final output of the training phase is the creation of a classifier.

The classification phase includes the identification of the collision status between the human and the robot (including its tools) based on the classified distance. Based on the confidence of the ConvNets [20], a score that depicts the matching rate of the unlabeled image to each class has been calculated. The scores are calculated for each class independently, while an unlabeled image can match with more than one classes. The class with the highest score indicates the distance between the human and robot. More specifically, the procedure incudes the classification of the collected images for each of the three cameras and eventually, the three dimensions in the space. Accordingly, there are three classes with the highest scores; one for each dimension. The three classes are compared and the minimum distance is selected as the classification output.

The retraining phase is optional and should take place in case that the classifier does not identify correctly the distances. For the retraining phase, another number of images should be collected foe each space dimension and to be labelled as it is described in the training phase. Then, a new classifier more accurate is created.

As for the generalization of the proposed framework to be deployed in cells with more than one robot, the same classifier can be used not only for one robot but for multiple robots. To achieve it, the captured images should be processed before the classification to be separated in smaller one which will include only one human and one robot each time. Then, the classification of the separated images will take place and the final output will arise as the total classification outcome of all the images which arise from the initial one.

4. Case Study

The proposed HRC enabling mechanism has been partially validated in a laboratory environment. To be specific, the experiment included the utilization of a camera sensor and a COMAU Racer robot. The robot was shut down for safety reasons. The camera was fixed in a stable rack enabling the image capturing for only one direction.

According the aforementioned approach, a number of image data with a human and a robot in the space was captured. These data were used to train an AI based models aiming to create a classifier. on. The implementation of AI model was performed using the IBM’s Watson Visual Recognition service. The IBM’s Watson is a question answering computing system based on the ConvNets architecture, built to be applied to many machine learning technologies. It can provide a very accurate and fast classification of the provided images because it packs a huge amount of processing power and memory, making it capable of 80 TeraFLOPs. When the AI model was trained, random image data were collected to examine the performance of the proposed HRC mechanism, even if in one space direction. The classifier output was a list of scores per labelled class; each class indicated one dimension between human and robot. In total 5 classes were created; one for 1 meter distance, one for 0.7 meter distance, one for 0.5 meter distance, one for 0.3 meter distance and one for collision state.

Regarding the experimentation, 20 experiments were performed in total with 16/20 success classification of the human-robot distance. The proposed model was not identifying successfully the 4/20 cases due to the camera view did not recognize the other two dimensions of the space. To be specific, the human was behind the robot without contact but the system could not identify it and the system results indicated the class “Collision”.

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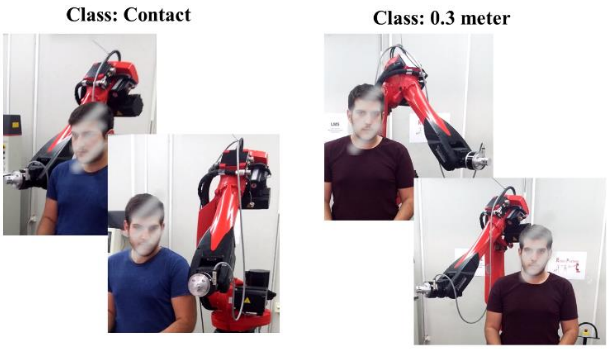

Fig. 6. Images and classification results from the experiments.

5. Conclusions and future work

The presented approach has been motivated by the current industrial trend towards safe human robot collaboration. It aims to present a HRC enabling mechanism based on AI models and vision systems able to identify the distance among human and robots in a shared workspace. One of the main advantages is that takes under consideration not only the robotic structure but the embedded/integrated tools or auxiliary devices. In this direction, the proposed concept promises a generic deployment in any kind of robots and workspaces using only 3 cameras as the main hardware modules. Its performance has partially been validated in laboratory while the potential reason which the system may fail to identify correctly the distance between robot and human was identified. Regarding the number of the images, 20 images per class (100 images in total) were sufficient for the first experimental analysis.

The future work will focus on the development of the proposed HRC enabling mechanism using a three-dimension vision system. As next, the coexistence of more than one human and robot in the same workplace will be investigated. Moreover, the investigation of other types of neural networks will take place to improve the system performance. Experiments with different backgrounds will also be examined to evaluate the system performant. Finally, the authors will focus on applying the suggested approach in the context of real industrial applications such as in assembly tasks involving human and robots.

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