

REAL-TIME ASSEMBLY OPERATION RECOGNITION

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ABSTRACT

This research is concerned to propose a computer vision algorithm to track manual assembly task. Manual assembly in case of electronics parts are used largely in automotive industry. The phases tracking of assembly could also be used for learning purposes such in case showed in this research, checking the assembly of an electronic educational board. The algorithms used for detection of different components are CNN (Convolutional Neuronal Network) as well as blob detection.

KEYWORDS: computer vision, assembly operation, recognition

1. Introduction

Manual assembly in case of electronics parts are used largely in automotive industry. The tracking of phases of assembly could also be used for learning purposes such in case showed in this research, checking the assembly of an electronic educational board. There are authors that used cameras such as Kinect® to investigate the position in 3D space of assembly line in order to assess there are minimum errors. Though robotics has advantages in industry, however manual assembly work cannot be avoided.

Recently concept in manufacturing Industry 4.0 underline the benefits using sensors on large scale and process in a "BIG DATA" set in order to extract best optimization for the industrial process. The data processed is used to eventually improve to maximum the manufacturing processes.

Nowadays, computer processing capabilities, as long with the computer vision algorithm available, allows the introduction of surveillance camera to be used on extensive scale in order to assess phases of assembly. There are previous works [1-6] attempted to utilize visual sensors to predict the pose in robotics task in assembly. Several researchers considered reconstructing 3D parts [7-10] in order to control the assembly process. At first glance, object recognition is very known topic in manufacturing with few challenges not solved. However, in case of assembly the identification and recognition of correct position of wires and parts with limited visibility while the operator is continuing the assembly process is a challenge. Object recognition is used in industry for decades for automated machine and robot to recognize parts and manipulate to certain position. The assembly process of electronic components such

as in case of automotive electric parts, we well as in case of surveillance for educational purposes showed important challenges. Many approaches of assembly surveillance are taking into account of identifying parts using features such as colour, specific shape and of course using artificial intelligence algorithm such as CNN (Convolutional neural networks) versus manual assembly task on a production line [11-13].

This research is concerned to propose a computer vision algorithm to track manual assembly task.

2. Experimental procedure

We considered that the camera is located 1.5 meters above the scene. The table height position allows a good estimation of proportion taking into account that electronic boards have low height. The illumination is variable, as in case of a school class, influenced by outdoor luminosity. The CNN network has trained with 50 images for each category: sensor, pin location (with the number written on the board) and electronic board.

We manually cropped every pin component along with the number written on the board. These specific classes cannot be found on public trained data base, except the electronic board.

Input images are resized to $224 \times 224 \times 3$ for matching the convolutional layer. Convolutional neuronal network identification is used for electronic board, pin location and sensor. The algorithm is depicted in Fig.1.

In order to identify the wire, we used blob identification considering the specific colours of the wires and shape. Several challenges occur in this stage in case the wire positioning is overlapping. The

task is composed of three steps, the wire connection of a sensor to the electronic board. Each step is assed at the end of each step (Fig. 2). The position of the hands is in a specific position as showed in Fig. 5. The recognition of this position triggers the computer vision assessment in order to determine the correct wiring. In this case there are specific ports where wiring should be done.

When the hands are in a specific position the software processes the scene. We need to stress some limitation in the proposed algorithm. Firstly, the algorithm is not considering important illumination variation. Secondly, for the educational application real cases, the input data could vary in an important manner concerning illumination.

3. Results and discussions

As discussed above, the proposed approach can be used in many domains, such as industry or for educational surveillance purposes. We show a proof-of-concept application utilizing simple testing case (Fig. 4). This research used a single web camera to assess assembly operations on an electronic board by recognition of wires position connection to specific pins. Each step of the assembly is processed only after the hands are allowing the camera to see the entire scene. Also, the background might be with variation of patterns. In case of industry, illumination could be maintained constant as well as the background. We used one single electronic board for training while the real case scenario should include different models.

Currently, the proof-of-concept application developed is tested with a limited data for the described specific assembly task.

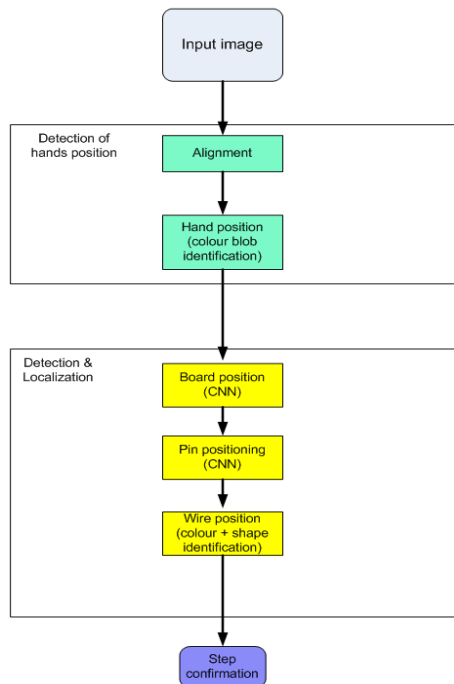


Fig. 1. Algorithm for scene understanding of assembly operation

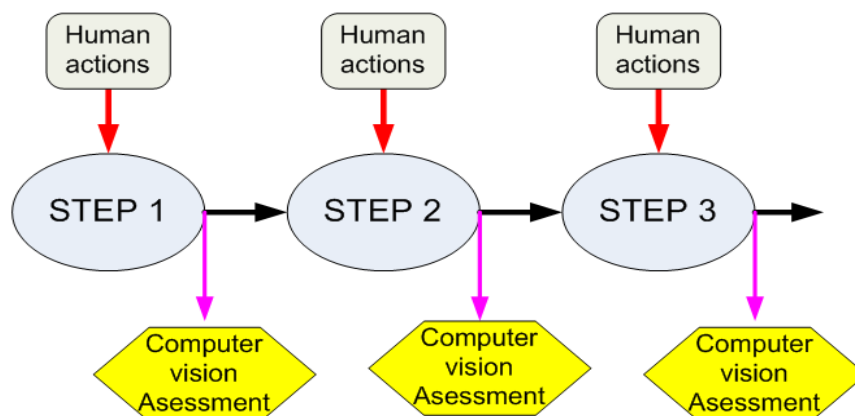


Fig. 2. The assembly steps surveillance

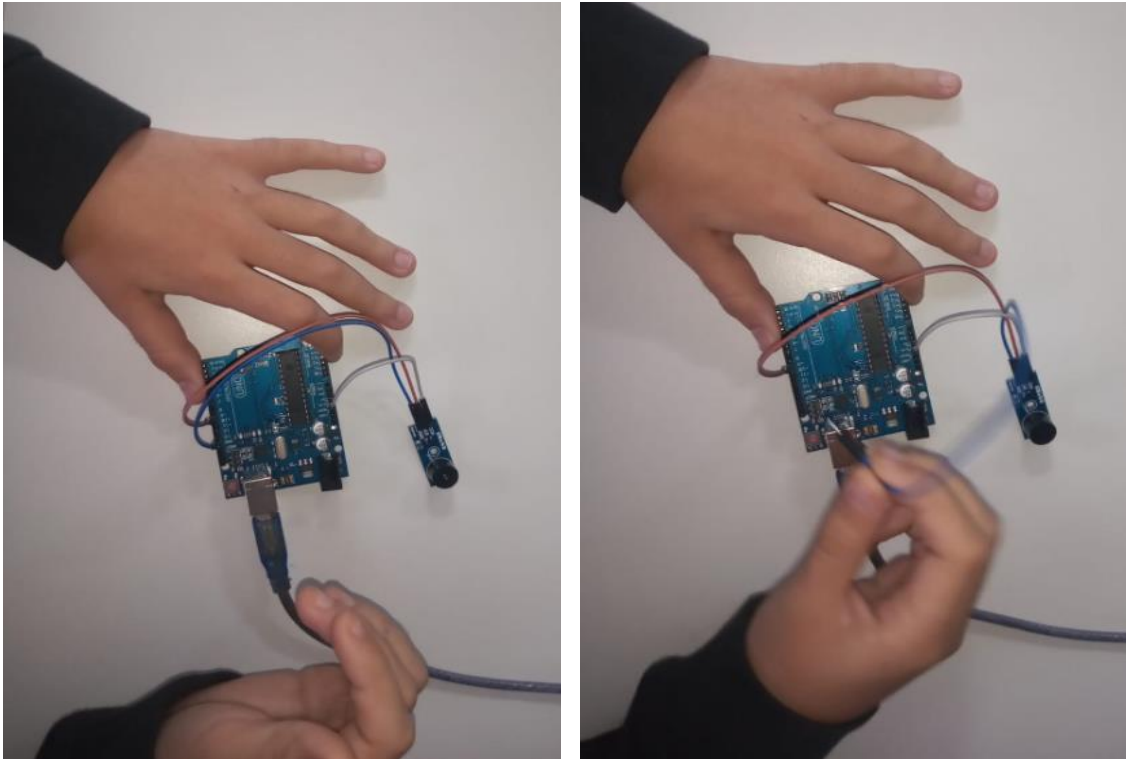


Fig. 3. Operation of assembly

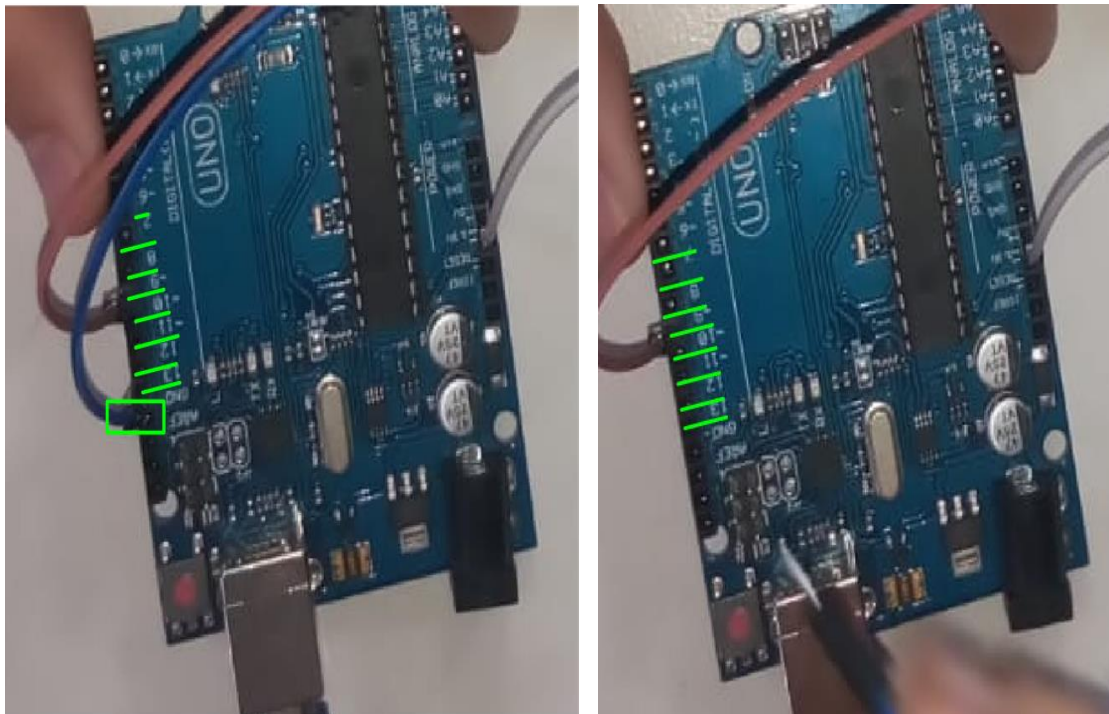


Fig. 4. Visualization of the pins location and wire connection

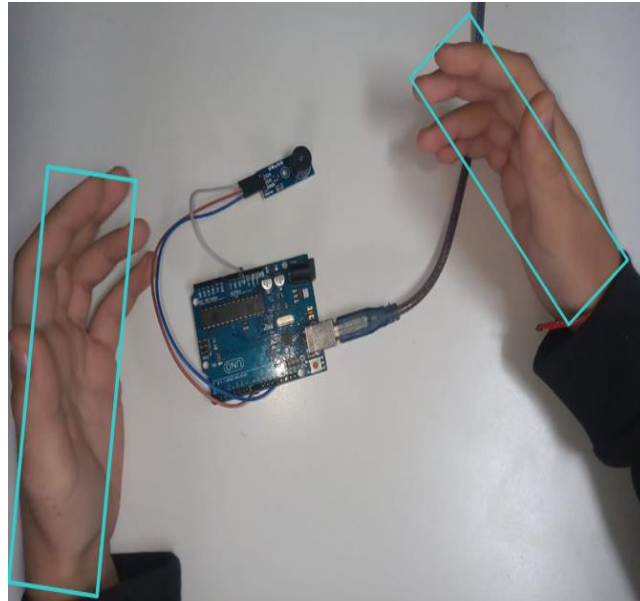


Fig. 5. Identification of hand position

4. Conclusions

The proposed algorithm is able to recognize position, no matter the rotation or position of the boards in the scene. It has been shown that it is possible to identify position of wires connected to specific pins on the boards. This was achieved by using shape identification using CNN to be carried out using different colour parts, such as in case of educational applications. Though only 2D image processing was used, the algorithm shows to be robust. Colour recognition of board was used as this is not subject to changes, such in case of industrial applications. Several advancements should be made for future development:

- 1) The algorithm capabilities should be tested by using a stereo vision;
- 2) Detection precision can be increased incorporating 3D part estimation rate.

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