An Automated Work Cycle Classification and Disturbance Detection Tool for Assembly Line Work Stations

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Abstract: The trend towards mass customization has led to a significant increase of the complexity of manufacturing systems. Models to evaluate the complexity have been developed, but the complexity analysis of work stations is still done manually. This paper describes an automated analysis tool that makes us of multi-camera video images to support the complexity analysis of assembly line work stations.

1 INTRODUCTION

In recent years, the market for manufacturing companies is shifting from mass production to mass customization. The increasing number of product variants leads to a significant increase of the complexity of manufacturing systems, both for the operator as well as for the manufacturing support systems. This problem has drawn the attention of a number of researchers in the last three decades. Some models to quantify the complexity in manufacturing environments have been developed, but most of the analysis is done manually.

One of the drivers of complexity in an assembly line work station, is the number of different work patterns in the work content. In this paper an automated method to evaluate and classify different work patterns is presented. Data is gathered by making a 3D reconstruction of the operator based on the images provided by multiple cameras.

2 LITERATURE REVIEW

As already mentioned, the trend towards more customized products induces a lot of challenges for manufacturing companies. Fisher et al. (1995), MacDuffie et al. (1996) and Fisher and Ittner (1999) investigated the effect of the increasing variety of products on the performance of producton systems in the automotive industry. Macduffie et al. (1996) stated that the part complexity is the only element that has a negative effect on the systems performance. Later on, it appeared that complexity is also driven by the way information is presented to the human in the system and the amount of information that person needs to process (ElMaraghy et al., 2003). They also proposed a methodology to evaluate product and process complexity and their interrelations. Most of the research concerning manufacturing complexity is trying to associate this complexity to product and process structures. Zeltzer et al. (2012) were the first to quantify the relationship between complexity and its drivers as perceived by the operator.

For years, industrial engineers have been using video images to facilitate and improve their work. Video sequences contain a lot of information and are a good way to document work methods (Karger and Hancock, 1982, Konz, 2011). Video analysis is also a well-used tool for method and time study. However, to perform detailed time studies, exact distances and measurements in the work place are needed. Elnekave and Gilad (2006) developed a rapid video-based analysis system that is able to translate distances accurately from the picture frame into real distance values of the workstation. Furthermore, video images can be used in training tools for operators, ergonomics analysis and the analysis of health and safety issues (Dencker et al.,

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1999). Nexteer, a supplier of automotive parts, uses a video analysis tool to facilitate the continuous improvement of their processes by comparing work methods of different operators in the same work station (Taylor, 2011).

A lot of work has already been done in the area of human behavior recognition using video images. Bodor et al. (2003) described a method to track pedestrians and classify their behavior in order to detect situations where people might be in danger. Computer vision and pattern recognition techniques are also widely used in video surveillance (Cristani et al., 2013). And although industrial engineers have been using video images for a long time, there is, to the best of our knowledge, no system to date that captures the behavior and activities of assembly line workers automatically.

3 IMAGE PROCESSING

To determine the position of the operator in the work station, the visual hull of his body is created for every frame in the video sequence. This visual hull is created by first constructing for each camera, a generalized infinity cone in the 3D space with the camera position being the apex and the silhouette in the camera view as the base. The 3D space is divided in voxels and only voxels that are within the infinity cones of all viewpoints, will be used to build up the 3D model of the operator (Laurentini, 1994). The objects center of mass is then projected onto the ground plane. This way we know the operators' position in every frame of the video image (50ms). The principle of voxel carving is visualized in Figure 1.

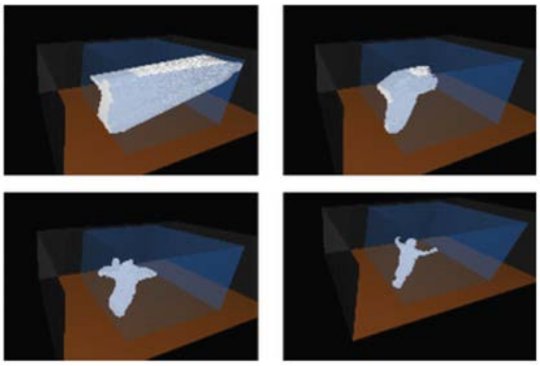

Figure 1: Voxel carving example.

One of the problems we face in industrial environments is occlusion. Static objects such as conveyers and racks make reconstruction very difficult. Therefore, a self-learning algorithm that is able to build an occlusion map for each camera from a voxel perspective, is developed. This information is then used to determine which camera viewpoints need to be taken into account when reconstructing the 3D model in every voxel in the scene. (Slembrouck et al., 2014)

4 TEST SET-UP

The experiments in this paper are done in a laboratory setup. In the experiments, the operator is asked to make some products out of Lego and Duplo blocks. The Duplo blocks, which serve as base for the assembly, are brought to the work station by a conveyer belt. This conveyer belt simulates a production line. On this base block, a pattern of smaller Lego blocks needs to be stacked.

Using Lego and Duplo has the advantage that we can easily create new scenario's with variable complexity (number of parts, variants, …). An example of a finished product is shown in Figure 2.

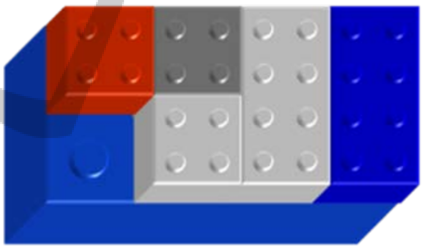

Figure 2: Finished part.

Parts (Lego) are stored at the border of line in a rack. The rack is equipped with a pick-to-light system. The work station is permanently equipped with 5 cameras, four of which are positioned in the top corners of the work station. The fifth camera has a fisheye lens and is positioned centrally above the workstation. A picture of the laboratory is shown in Figure 3.

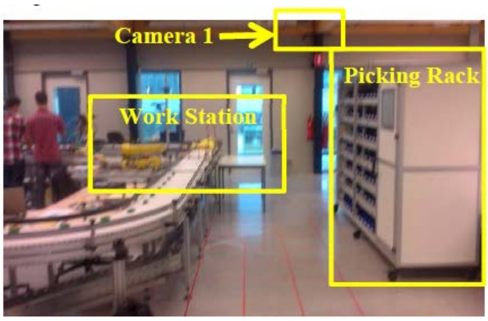

Figure 3: Picture of the laboratory setting.

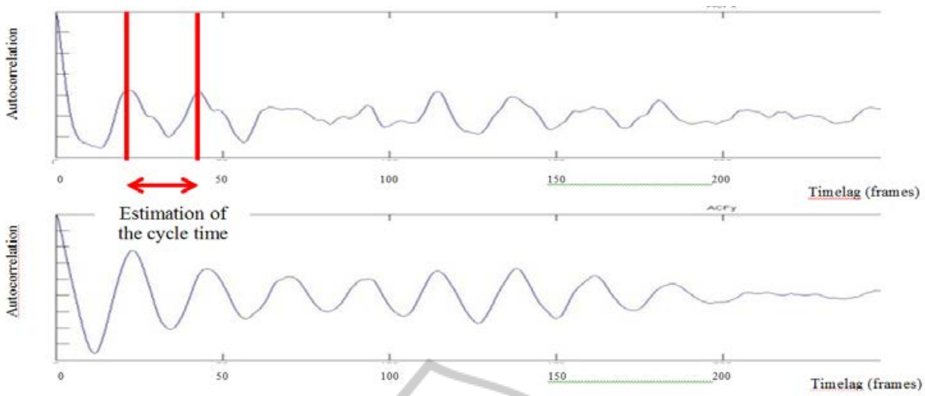

Figure 4: Autocorrelation functions.

5 WORK CYCLE CLASSIFICATION

5.1 Cycle Time Analysis

High complexity in the work content induces variation in the cycle time. To determine the cycle time in a work station and the variation of this cycle time, we need to divide the data into work cycles. A first estimation of the cycle time can be made using the autocorrelation function of the operators' path.

5.1.1 Autocorrelation

The autocorrelation shows the similarity between observations as a function of the time lag between them. In this case, the distance between two peaks in the autocorrelation function gives an indication of the time the operator needs to return to a previously visited location. The x- and y component of the autocorrelation function for one scenario are shown in Figure 4.

Sometimes there are several 'local' peaks in the autocorrelation function. To eliminate this noise, we only keep the maximum value of the autocorrelation function within a certain time frame. This time frame is increased until the cycle time based on the x-component matches the one calculated using the y-component.

5.1.2 Segmentation

The autocorrelation function gives an indication of the cycle time. However, to know the real cycle time, we need to segment the data in separate work cycles. To do this, we assume that the operator starts his work by picking parts at the border of line. Afterwards he goes back and performs all assembly actions needed to finish the assembly. To determine the start of a work cycle, the work place is divided in several zones. A work cycle starts when the operator leaves the assembly zone.

After segmentation, the duration of every work cycle is determined. The results of this analysis are displayed as a SPC-chart in Figure 5.

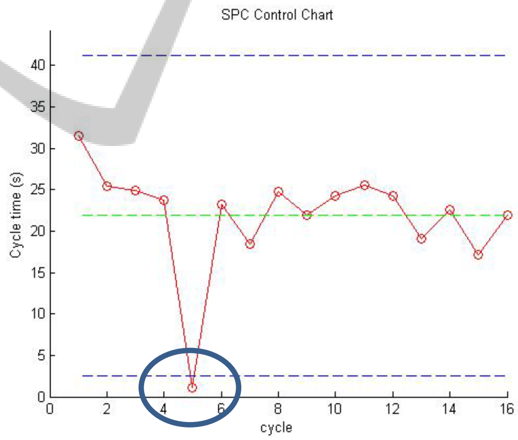

Figure 5: Segmentation based on location only.

Segmentation purely based on the location of the operator however, appears to be flawed. The operator sometimes leaves to assembly zone for a short amount of time, for instance to set right a picking mistake he made. To avoid that these short events are considered to be a separate cycle, we assume that the shortest real cycle in a work place will take at least half of the time of the average work cycle. We compare the cycle time of every segment to the previously calculated average cycle time and add short cycles to the previous segment. This way, short disturbances are not treated as a separate segment. The segmentation process is shown in Figure 6.

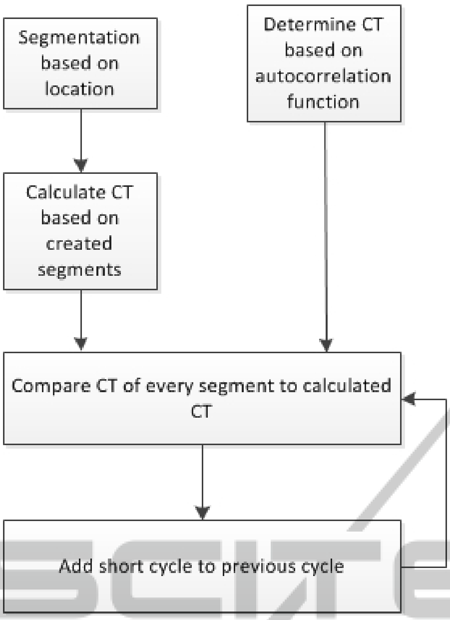

Figure 6: Segmentation procedure.

Figure 7 shows the control chart for the same scenario as Figure 5 after using the new segmentation procedure.

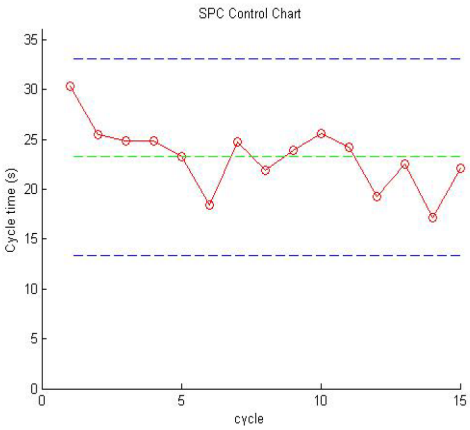

Figure 7: Segmentation using new segmentation procedure.

5.2 Work Patterns

The complexity of the work content increases with an increasing number of work patterns the operator has to remember. Therefore, a procedure to cluster the segmented data into groups of similar work patterns was developed.

5.2.1 Work Cycle Clustering

A very simple and fast way of clustering data is k-means clustering. There is however one big disadvantage to this method: the number of clusters needs to be known in advance. Since we don't know how many work patterns (clusters) there are, we choose to classify the segments using hierarchical clustering. The outline of the hierarchical clustering algorithm is given in Figure 8.

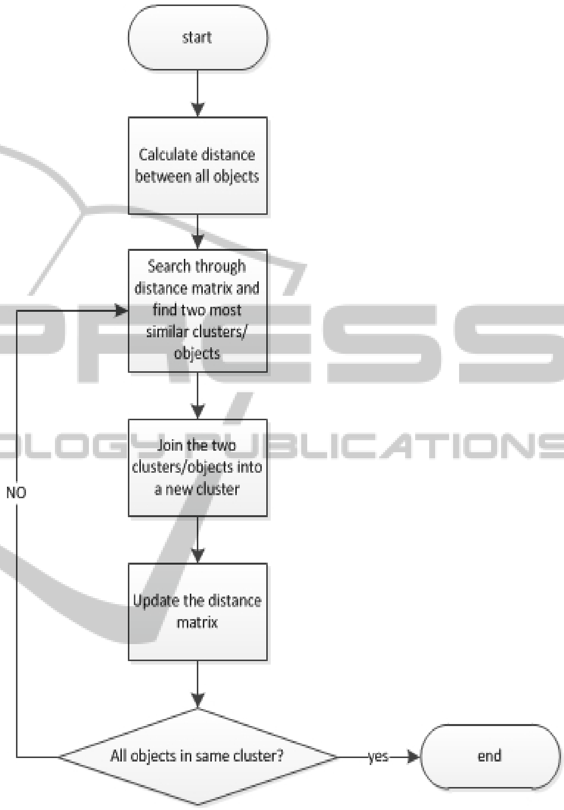

Figure 8: Hierarchical clustering.

To calculate the distance matrix, we cannot simply use the Euclidean distance between all points of two cycles. The first reason for this is that the cycles have different lengths. And even if all cycles would have the same length, using Euclidean distance would not give us any useful information because it cannot cope with the fact that the operator can do the same work cycle at different speeds. To overcome this hurdle, we use a technique called dynamic time warping (DTW) to calculate the similarity between segments of data.

5.2.2 Dynamic Time Warping

Dynamic time warping is a technique that is used a lot in the analysis of time series, such as temporal sequences of video and audio. It is a technique that measures the similarity between two time series which may vary in speed. DTW is capable of recognizing similar work patterns, even if the operator is performing the same task at different speeds.

DTW calculates the best match between two time series with three important restrictions: (Müller, 2007)

- Monocity: The alignment path does not go back in time
- Continuity: The alignment path does not jump in time
- Boundary conditions: Makes sure the alignment doesn't consider one of the sequences partially

Figure 9 visualizes the alignment between to two-dimensional time series using the dynamic time warping algorithm.

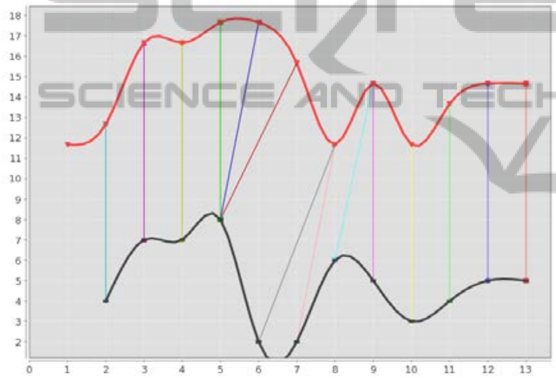

Figure 9: Visualization of DTW procedure (from: http://math.ut.ee).

5.3 Cycle Time Analysis

5.3.1 Scenario 1

In this scenario, the operator was given the task to produce 15 end products of 2 variants. The first variant was a low complexity assembly using only 2 different parts. All parts for this variant were stored at the right side of the border of line and 12 of these products were produced. The second variant consists of 5 different parts which were stored at the left side of the rack. Only 3 products of this variant were made. The 15 work cycles are shown in Figure 10.

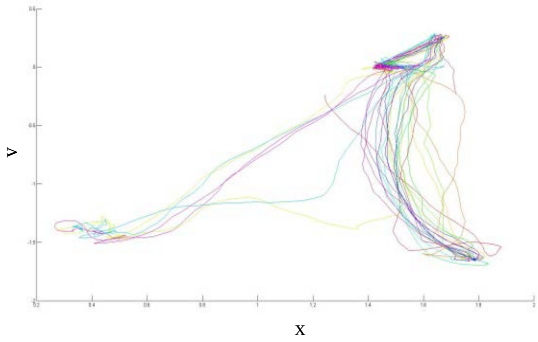

Figure 10: Path of the operator in scenario 1.

5.3.2 Results

As we could expect, there is a significant difference in cycle time between the cycles where variant 1 was produced and those where variant 2 was made. This is shown in the SPC-chart in Figure 11. It appears that variant 2 was produced in work cycles 4, 9 and 14, which corresponds to the task sequence the operator was given.

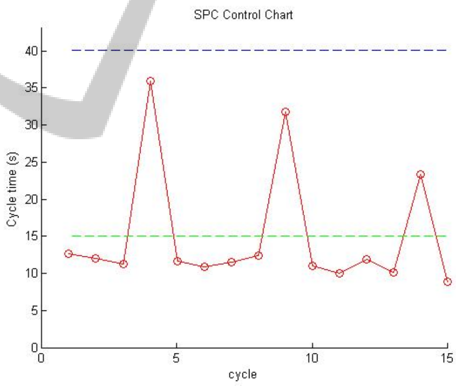

Figure 11: SPC scenario 1.

Clustering this data using the techniques mentioned earlier, results in following dendrogram, which clearly shows that there are 2 main clusters and that cycles 4, 9 and 14 are classified in the same cluster.

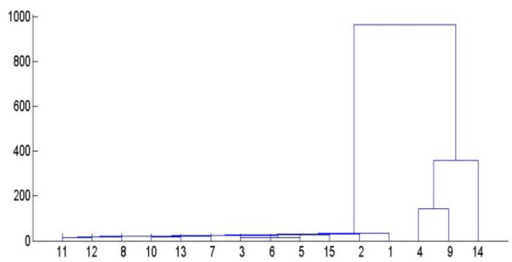

Figure 12: Dendrogram scenario 1.

5.3.3 Scenario 2

The two work patterns in the scenario above are significantly different. In a new scenario the operator was asked to make the same product 9 times. Some of the parts in the bins were taped so they could not be assembled. In that case, the operator had to go back and pick that one part again. The results of the clustering analysis are shown in Figure 13. We can see clearly that the analysis tool is capable of detecting irregularities in the work pattern.

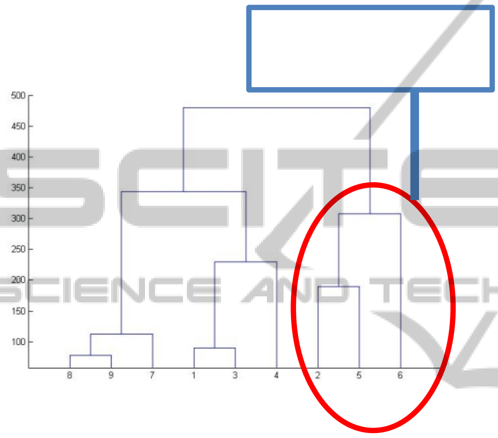

Figure 13: Dendrogram scenario 2.

5.3.4 Scenario 3

In a third and last scenario, two operators were asked to perform the same task sequence. One of the operators was asked to follow the borders of a grid that was taped to the ground. This results in a very structured walking pattern. The second operator did not get any extra instructions. Both patterns are shown in Figure 14 below.

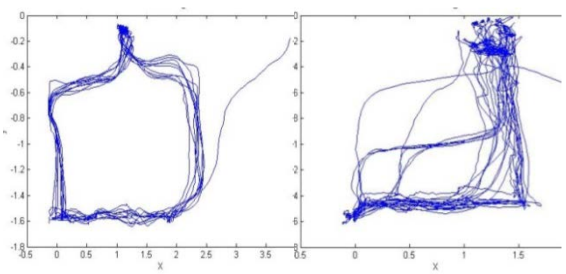

Figure 14: different work patterns scenario 3.

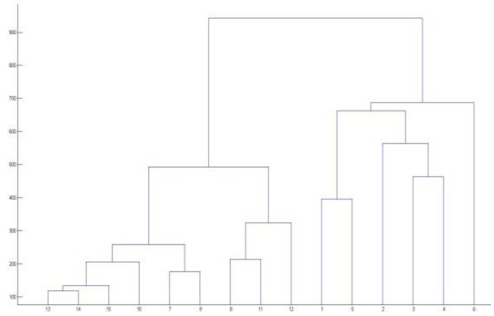

Figure 15: Dendrogram scenario 3.

Figure 15 shows the dendrogram for this scenario. Again we can see a clear division into two clusters. Also the disturbances in the second pattern can be detected in the plot.

6 CONCLUSIONS

In this paper we presented an automated tool that supports the complexity analysis of assembly line work stations based on the images from multiple cameras. The research shows that the current image processing technology can help us to automate the analysis of assembly line workstations.

A method to segment data into work cycles and classifying these cycles using hierarchical clustering was proposed. This technique is capable of differentiating between different work patterns and detecting disturbances.

All results in this paper are based on experiments done in a laboratory setting. In the future, we will do a field test in a real production scene. The use of the image processing technology in manufacturing environments should not be limited to the analysis of complexity in work stations. In the future, an efficiency and ergonomics analysis module could be added to the analysis tool in order to provide industrial engineers with a lot of useful information.

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