EXPLOITING VISUAL OBSERVATIONS FOR EFFICIENT WORKFLOW SCHEDULING IN PRODUCTION ENVIRONMENTS

Anastasios Doulamis
Technical University of Crete, D5 building, University Campus, Chania, Greece

Keywords: Visually observed industrial operations, Workflow scheduling, Tracking, Incremental spectral clustering.

Abstract: This paper proposes a new production scheduling algorithm that exploits (a) visual observations of industrial operations to estimate the actual completion times for tasks and (b) incremental graph partitioning-based clustering algorithms. The latter are implemented through an incremental implementation of the spectral clustering. Computer vision tools are applied to identify industrial operations via visual observations.

1 INTRODUCTION

Production scheduling/planning is probably one of the most critical managerial tasks within an industry with many benefits for the production. In particular, it (i) can determine whether delivery promises can be met and identify time periods for preventive maintenance, (ii) gives personnel an explicit statement of what should be done so that supervisors and managers can measure their performance, (iii) minimizes the average flow time through the system, (iv) minimizes setup times and (v) maximizes machine and/or worker utilization.

The main difficulty of production scheduling/planning stems from the fact that many real-world manufactories are complex in nature and it is a real challenge to find an efficient scheduling method that satisfies the production requirements as well as utilizes the resources efficiently. To overcome these difficulties, simulation approaches have been proposed to "model" complex real-world systems. Simulations develop models for generating detailed plans to control the real-world industrial operations. However, usually the real world (severely) differs than the idealized computer models so that scheduling/planning derived through simulation (significantly) deviates from the actual conditions.

One possible way to monitor current processes/operations is through the use of Radio Frequency Identification -RFID sensors (Gonzalez Fernandez et. al, 2010) (Ilic et al., 2010). These, however, are efficient only for specific industrial environments, while their reliability under harsh industrial conditions is questionable. Another possibility is the use of cameras. Nevertheless, cameras that do not support machine learning technologies and computer vision methods actually result in a manual survey of the industrial operations fact that eliminates any possibility for a dynamic (non-rigid) industrial planning. It is impossible for the survey employees to continually concentrate on monitors that display different activities in different areas. Additionally, there is a subjective interpretation as far as humans' behaviours are concerned, let alone additional cost and exploitation of humans' resources.

The recent advances in computer vision and machine learning society have endowed the cameras with smart capabilities. They can detect salient objects, track moving entities, interpret important events taking place in the industry and finally adapt their performance to environmental changes. Thus, they can endow modern factories with new cognition capabilities transforming them to "smart industries". Most of the current approaches for industrial scheduling exploit concepts derived from computational processors (Shaik et. al. 2007), (Drotos et; al., 2009). The incorporation of computer vision tools able to understand the actual (real-time) execution of industrial processes is rather limited. A survey of industrial vision systems has been reported

Doulamis A..
EXPLOITING VISUAL OBSERVATIONS FOR EFFICIENT WORKFLOW SCHEDULING IN PRODUCTION ENVIRONMENTS.
DOI: 10.5220/0003305905310537
In *Proceedings of the 3rd International Conference on Agents and Artificial Intelligence* (ICAART-2011), pages 531-537
ISBN: 978-989-8425-40-9

in (Malamas et. al., 2003), while extraction of salient features for defining and detecting industrial events has been discussed in (Motai, 2005). Assistance towards an efficient visual supervision of an industrial plant can be achieved by exploiting distributed cameras as well as communication issues among them (Karakaya and Hairong Qi, 2009). Surveying industrial tasks and workflows using web services has been presented in (Idoughi et. 2010). The main objective of that work is to handle complex and concurrently executed services on large-scale industries. The adoption of Service Oriented Architectures (SOA) and the use of web services enable a flexible and transparent interaction between the field devices and human operators (Doulamis and Matsatsinis, 2011).

In this paper, we propose a new production scheduling algorithm which is related on defining events, actions and workflows on visual surveyed areas of an industry. The algorithm is based on a new dynamic spectral clustering methodology. This means that instead of using the conventional spectral clustering algorithm (Bach and Jordan, 2004), we adopt a modified version of it so that dynamic arrivals of tasks' workflows and dynamic deviations of the actual to the estimated completion times are allowed (Huazhong Ning et. al, 2010).

In particular, the proposed algorithm initially statically schedules the submitted industrial workflows by constructing a graph whose nodes refer to the industrial operations while the edges to the non-overlapping degree among the tasks. The main, however contribution of the presented paper is the fact that it incorporates computer vision and pattern recognition algorithms in the industrial process so as to approximate as much as possible the actual completion times of the already executed tasks, or in other words, to estimate possible deviations between the actual and the requested completion times. To accomplish this,we introduce visual trackers able to self-correct their performance with respect to environmental changes (Section 4), and part-to-whole curve matching techniques (Section 5), so as to estimate the delays or accelerations in the actual task execution.

2 OVERVIEW OF PROPOSED ARCHITECTURE

Figure 1 shows an overview of the proposed industrial scheduling algorithm which exploits events analysis and detection tasks. Initially, we consider that the requested start and finish times for a set of industrial operations are available to the architecture. Based on this static information, we calculate the overlapping degree among the submitted tasks (or equivalently the non-overlapping degree). Then, we construct a graph and we solve the static scheduling problem as a graph partitioning problem considering the spectral clustering algorithm (Bach and Jordan, 2004). At this point the process resembles our earlier work of (Delias et. al, 2011) in which the spectral clustering algorithm has been adopted to allocate complex business workflows into the available resources. However, this results in a static scheduling.

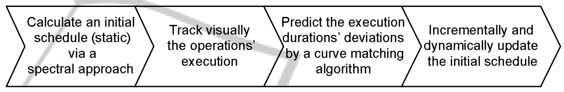


Figure 1: Overview of the methodology.

In this paper, we improve the static workflows scheduling by incorporating computer vision algorithms in the process. In particular, a set of cameras' sensors observe the trace of an industrial task as it is executed by the workers. This identification is carried out by the use of a tracking algorithm, which "observes" the industrial processes by tracing the trajectory that the persons follow. For tracking, a new self-initialized tracking algorithm is proposed to trace the trajectory of the moving objects in a scene. The algorithm automatically selects new confident data from the current image frame whenever the tracker performance is not adequate so as to re-initialize its performance, and thus to improve the object's tracing in harsh industrial environments. Towards this direction, we propose a modification of the data selector algorithm of (A. Doulamis, 2010) so as to be robust to industrial applications by using an adaptive non-linear classifier (Section 4). A modification of (A. Doulamis, 2010) has been also proposed in (Doulamis and Matsatsinis, 2011) to fit the particularities of an industrial environment. However in (Doulamis and Matsatsinis, 2011), linear adaptive methodologies are proposed in contrast to the current work.

Then, we apply a curve matching algorithm to predict the deviations of the estimated execution durations based on the visual observations. Part-to-whole curve matching methods are implemented so as to estimate the current completion time for executing a job based on the current on-going process. Instead of the part-to-whole approach adopted in the Service Oriented Architecture of

(Doulamis and Matsatsinis, 2011), in this paper, a guided search algorithm is adopted to improve the minimization of the optimal criterion so that better matched points are firstly identified.

Apart from the computer vision and pattern analysis techniques, a new dynamic scheduling algorithm is applied to take into account the dynamic modifications of the start and finish times for the executed tasks. This is achieved in this paper by incrementally refining the static scheduling results (Huazhong Ning et. al, 2010). Instead, the "from scratch" application of a static spectral scheduling algorithm would be computationally very expensive, making its use preventable. We also extend the work of (Doulamis and Matsatsinis, 2011) by proposing an optimized method for data scheduling in terms of dynamicity and optimality.

3 SPECTRAL CLUSTERING FOR SCHEDULING INDUSTRIAL WORKFLOWS

Assuming that we have calculated the requested start (S_i) and finish times (F_i) for the ith workflow W_i (let N be the total number of operations contained in all the workflows), we can model their relations as an indicator of their overlapping, say $a_{i,j}$. Instead of (Delias et. al, 2011) in which the $a_{i,j}$ is defined as a binary measure, in this paper we adopt a continuous modification of the overlapping measure to make it more robust to the dynamic changes. This means that

$$a_{i,j} = \begin{cases} 0 \text{ if operations } i \text{ and } j \text{ overlap} \\ \varphi \text{ otherwise} \end{cases} \tag{1}$$

We introduce two objective optimization criteria, which can measure the plan's efficiency with respect to the overall goal. The first one is associated with the violation of the deadlines. The corresponding optimization criterion is mathematically formulated as

$$V_m = \frac{\sum\limits_{i \in O_m, j \notin O_m} a_{i,j}}{\sum\limits_{i \in O_m, j \in W} a_{i,j}} \tag{2}$$

where m indicates that the optimization metric refers to the mth resource, O_m is the set of the operations that is planned for allocation to the m^{th} resource, and W is the set of all the operations that require to be executed. Additionally, V_m is a marginal optimization criterion. The overall criterion is calculated by the summation of these marginal criteria over all the available resources M, and as stated before, an efficient scheduling plan should keep it at a minimum value.

The second optimization criterion concerns the thriftiness of the plan, namely how resources should be utilized so as to prevent wasteful schedules. This criterion can be mathematically expressed as

$$U_m = \frac{\sum\limits_{i \in O_m, j \in O_m} a_{ij}}{\sum\limits_{i \in O_m, j \in W} a_{ij}} \tag{3}$$

Once again U_m is a marginal optimization criterion (with respect to the m^{th} resource). The overall criterion is calculated similarly with the deadlines' violation criterion, i.e., as the sum of all the U_m over all the M available resources.

As it is shown in a previous work (Delias et. al, 2011), it is possible to jointly optimize the above mentioned criteria through the use of the Ky-fan theorem (Ky Fan, 1951).

Actually, the solution matrix S needs an additional step to provide a schedule, as it contains real values while the assignment method requires for values which are either 1 /0. In this paper, we initially apply the above mentioned methodology to get a first approximate estimate for the production schedules, that is, a schedule based on the requested start and finish times.

4 SELF CORRECTED TRACKING FOR INDUSTRIAL PROCESSES

In this paper, we modify the self initialized tracker of (A. Doulamis, 2010) so as to be appropriate for industrial applications. More specifically, the architecture of (A. Doulamis, 2010) is only adequate for scenes that contain moving objects. This is not, however, an industrial case since workers can remain almost still for a relatively long time interval in order to fulfil some of their activities. In addition, the background complexity of an industrial environment imposes significant deviations from a good performance.

To address this difficulty, in this paper we modify both the data selector module of (A. Doulamis, 2010) and the object labelling adapter. In particular, a non-linear classifier is proposed as an efficient background model, which in the sequel is used as a more suitable data selector. The classifier is based on a neural network structure. Neural network-based background modelling has been also proposed in (Culibrk et. al, 2007). The weights, however, of the classifier do not remain static but they are modified during the video streaming so that the model can be adapted to the dynamics of the current conditions. This is achieved in our algorithm via the object labelling adapter. In (Culibrk et. al. 2007), the observed statistics are exploited to dynamically modify the neural network weights, while in this paper an optimal network retraining strategy is adopted as in (Doulamis A. D et. al, 2000).

More specifically, initially the Gaussian Mixtures are used to give approximate estimates of the background content. These mixtures are automatically updated from frame to frame to capture small and/or periodic modifications of the visual content on the background. As we have stated above, the neural network classifier is actually used for separating the foreground region from the background based on a non-linear mapping of the Gaussian mixtures information with respect to the specific background content. However, since the background is modified from frame to frame the weights of the neural network classifier cannot be considered constant. Instead, they should be updated. The generalized neural network retraining algorithm of (Doulamis A.D et. al, 2000) is adopted in this paper for an optimal updating of the network parameters. With respect to our knowledge, this is the first time that a non-linear and dynamic classifier with optimal retraining strategies will be applied for background content modelling. In addition, the exploitation of the self initialized architecture of (A. Doulamis, 2010) for the purpose of an industrial plant constitutes another contribution of the proposed work.

5 ESTIMATING THE ACTUAL WORKFLOWS COMPLETION TIMES

In this paper, we modify the technique of (Cui et. al, 2009) by applying guided search in order to find the most appropriate correspondence points among the two curves. This is due to the fact that the main challenging issues of our partial to whole match approach is that we do not know the last point of the partial curve but only the first (start) one. This is due to the fact that we do not know the current execution time.

In particular, we initially model both curves using the integral of the curvature measures, i.e., the integral of the norm of the second derivative,

$$C(s_1 : s_2) = \int_{s_1}^{s_2} \left| s''(x,y) \right| ds \tag{4}$$

where $s''(x,y)$ is the second derivative of a curve, that is either of t or of f. In (Cui et. al, 2009), it is proved that $C(s_1 : s_2)$ is invariant under a similarity transform. Thus, this measure can be used to represent the curve complexity. However, it is still problematic to match parts of two curves, sine the starting value of the integral of (4) can be of any number.

To solve this problem, we initially consider that the curvature points, as well as their averaging, are the most characteristics points of the curve. Then, we use a cross correlation criterion as a similarity matching for both curves. In particular, if we have defined the most appropriate last point of curve f, then we could take a part of it starting from the first point to the last one and find its correlation to the traced curved t. Let us denote as $P_0(f), P_{last}(f)$ the first and the last point of curve f and as $P_0(tr), P_{last}(tr)$ the respective first and last point of curve t. Then, the correlation coefficient can be considered as a measure for their matching.

$$\begin{aligned} &Corr(P_{last}(f), P_{last}(tr)) = \\ &= \frac{[f(P_o : P_{last}) - \mu(f)] * [t(P_o : P_{last}) - \mu(t)]}{\sqrt{[f(P_o : P_{last}) - \mu(f)]^2 * [tr(P_o : P_{last}) - \mu(t)]^2}} \end{aligned} \tag{5}$$

In equation (5), $f(P_o : P_{last})$ refers to a part of the f curve starting from $P_0(f)$ and ends to $P_{last}(f)$. Similarly, we define the $tr(P_o : P_{last})$ curve. The function $\mu(\cdot)$ returns the average of each curve. It is worth to note that *Corr* function actually depends on the last points of both curves since the first ones are already available and known.

Then, the optimal last point of f is found through the following minimization

$$\hat{P}_{last}(f) : \max_{P \in S_f} \{Corr(P_{last}(f), P_{last}(tr))\} \tag{6}$$

A genetic algorithm is adopted then to find an optimized solution to the above mentioned minimization problem.

6 UPDATING THE SPECTRAL CLUSTERING

The proposed scheduling algorithm although very efficient, is computationally expensive to be used from scratch in every case that the start or finish times are modified. There is a need to exploit the updated information that comes from the visual tracker and the curve-matching algorithm with a fast yet reliable way. In this paper the following approach is proposed: Since the visual tracker and the curve-matching algorithms detect modifications in the normal workflow (i.e., modifications of the start and finish times of the operations), the initial affinity matrix of operations which indicates the overlapping among the operations is modified as well. In fact, only some distinct elements of the affinity matrix are affected. These changes may induce alterations to both the degree matrix D and the eigenvectors matrix E. As it is proved in (Huazhong et. al, 2010), it is possible to approximate the increment of the eigenvalues and the eigenvectors, without needing to re-solve the generalized eigenvalue problem.

The exact sub-process of the incremental update is described by the following steps:

(a) Get informed about the modified start and finish times of operations (via the visual tracker and the curve matching algorithm),

(b) Update the affinity (overlapping indicators) matrix according to the new overlapping conditions,

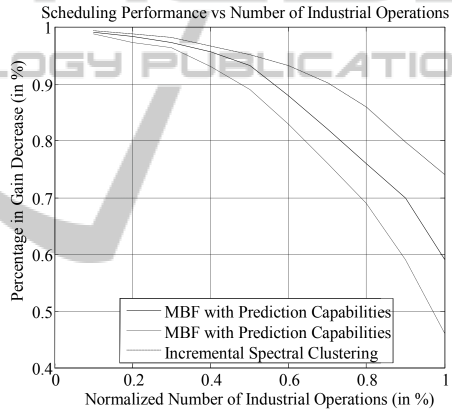
(c) Iteratively refine matrices E (eigenvectors) and D (degree). (d) Apply the k-means algorithm to the updated solution matrix S and get the new schedule.

7 EXPERIMENTAL RESULTS

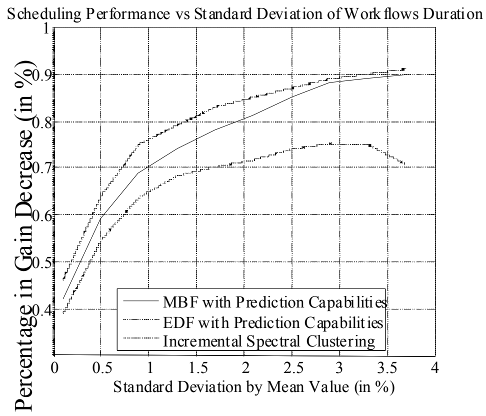
Our experiments are carried out on a real-life industrial environment, the one of *Nissan Iberica* Automobile Construction company in Barcelona Spain. The dataset collected include three full days video capturing in the industry that describe any complex activity (www.scovis.eu).

Figure 2 shows the tracking results using the proposed modified self corrective algorithm. The boxes have been shown in black colour. Similarly, Figure 2 compares the tracking performance using the methodology described in (Doulamis and Matsatsinis, 2011) (with yellow colours). As we can observe, a slightly better tracking improvement is derived in our case than when the algorithm of (Doulamis and Matsatsinis, 2011) is used. We need to stress that the original performance of the self initialized algorithm of (A. Doulamis, 2010) gives much more worsened results in such complex industrial cases.

Figure 2: The tracking performance of the proposed algorithm (black boxes) as being compared with the results of the (Doulamis and Matsatsinis, 2011) approach (yellow boxes).



(a)



(b)

Figure 3: Comparison of scheduling performances.

In the following, we compare the performance of the proposed incremental spectral clustering algorithm with the heuristic method of Maximum Benefit First (MBF), proposed in (Doulamis and Matsatsinis, 2011) and the Earliest Deadline First (EDF) algorithm. We follow the same setup as in (Doulamis and Matsatsinis, 2011). In particular, we divide the total scheduling time horizon into 10 uniform intervals and we randomly generate 100 operations per interval, i.e., we totally create 1000 workflows. At each interval the scheduler is activated to assign to resources the already submitted workflows (the 100 newly generated and the ones that have not been assigned / executed yet). The start and finish times of the operations are uniformly distributed within three time intervals starting from the current one. We set as delivery deadline per each operation a 20% time extension beyond its finish time. Furthermore, we consider that each operation completed before its deadline yield the economic gain to the industry which also follows a normal distribution, while each violation of the operations deadline burdens with a constant compensation of 20% of the maximum gain among all workflows. This means that negative cost (damages) can be derived.

Figure(a) shows the scheduling efficiency derived by the use of the proposed incremental spectral clustering algorithm and the MBF method of (Doulamis and Matsatsinis, 2011) versus the number of operations. This number has been normalized with respect to the maximum number of 1000 for clarity purposes. We observe that the proposed algorithm schedules better the operations than the method of (Doulamis and Matsatsinis, 2011). We need to recall that this algorithm deviates from (Huazhong Ning et. al, 2009) in the sense that, due to the different nature of our problem, incremental clustering should be followed. To emulate the effect of the computer vision tools we assume a delay on the 80% of the already executed operations which is uniformly distributed between the requested finish time and a 100% extension of it. The remaining 20% of the currently running workflows are left intact.

In these results, we have randomly generated workflows of Gaussian probability density function (pdf) which present a standard deviation equal to their mean value. The effect of the proposed scheduling scheme versus standard deviation values is depicted in Figure(b). In this Figure, we have also presents results obtained apart from the MBF along with the EDF algorithm as well.

ACKNOWLEDGEMENTS

The author would like to thank SCOVIS, "Self Configurable Video Supervision" European Union Project for providing the data sets results and its support to this work.

REFERENCES

Gonzalez Fernandez, J., Yelmo Garcia, J. C., Martin Garcia Yo.-S., and de Gracia Santos J., "Transf-ID: Automatic ID and Data Capture for Rail Freight Asset Management", *IEEE Internet Computing Mag.* Jan./Feb. 2010.

Ilic, A., Andersen, T., and Michahelles, F., "Increasing Supply-Chain Visibility with Rule-Based RFID Data Analysis", *IEEE Internet Computing* Jan./Feb. 2010.

Shaik, M. A., Floudas, C. A., Kallrath, J., Pitz, H.-J, "Production scheduling of a large-scale industrial continuous plant: Short-term and medium-term scheduling," *Computer Aided Chemical Engineering*, Vol. 24, pp. 613-618, 2007.

Drotos, M., Erdos, G., Kis, T., "Computing lower and upper bounds for a large-scale industrial job shop scheduling problem," *European Journal of Operational Research*, Vol. 197, No,1, pp. 296-306, August 2009.

Malamas, E. N., Petrakis, E. M., Zervakis, M., Petit, L., Legat, J.-D., "A survey on industrial vision systems, applications and tools," *Image and Vision Computing,* Vol. 21, No. 2, pp. 171-188, 2003.

Motai, Y., "Salient feature extraction of industrial objects for an automated assembly system," *Computers in Industry*, Vol. 56, Nos. 8-9, pp, 943-957, December, 2005.

Karakaya M. and Hairong Qi, "Target Detection and Counting using a Progressive Certainty Map in Distributed Visual Sensor Networks," *3rd ACM/IEEE International Conference on Distributed Smart Cameras*, ICDSC 2009.

Idoughi, D., Kerkar, M., Kolski, C., "Towards new web services based supervisory systems in complex industrial organizations: Basic principles and case study," *Computers in Industry*, Vol. 61, No. 3, pp. 235-249, 2010.

Doulamis A., and N. Matsatsinis, "Visual Understanding Industrial Workflows under Uncertainty," submitted to the *Future Generation Computer Systems Journal.*

Bach F. R., and Jordan M. I., "Learning spectral clustering," In S. Thrun, L. Saul, and B. Schoelkopf (Eds.), *Advances in Neural Information Processing Systems* (NIPS) 16, 2004.

Huazhong Ning, Wei Xu, Yun Chi, Yihong Gong and T. S. Huang "Incremental spectral clustering by efficiently updating the eigen-system," *Patter Recognition,* Vol. 43, No. 1, pp.113-127, 2010.

Delias, P., Doulamis A., Doulamis N., and Matsatsinis N., "Optimizing Resource Conflicts in Workflow," *IEEE Trans. on Knowledge Engineering,* accepted for publication.

Doulamis A., "Dynamic Tracking Re-Adjustment: A Method for Automatic Tracking Recovery in Complex Visual Environments," *Multimedia Tools and Applications,* Springer Press, 1380-7501 (Print) 1573-7721 (Online).

Ky Fan, "Maximum properties and inequalities for the eigenvalues of completely continuous operators," *Proceedings of the National Academy of Sciences* pp. 760–766, 1951

Culibrk, D., Marques, O., Socek, D., Kalva H., Furht, B. "Neural Network Approach to Background Modeling for Video Object Segmentation," *IEEE Trans. on Neural Networks*, Vol. 18, No.6, pp.1614-1627, Nov.2007.

Doulamis A. D., Doulamis N. D. and Kollias, S. D., "On Line Retrainable Neural Networks: Improving the Performance of Neural Network in Image Analysis problems," *IEEE Trans. on Neural Networks*, Vol. 11, No. 1, pp. 137-155, January 2000.

www.scovis.eu

Cui, M., Femiani, J., Hu, J., Wonka, P., Razdan, A., "Curve matching for open 2D curves," *Pattern Recognition Letters*, Vol. 30, pp. 1–10, 2009.