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Trend-specific clustering for micro mass production of linked parts

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1. Motivation

Optimizing processes require increasing effort, as tolerances of parts become tight. The advantage of assembling out of the box justifies the effort in many cases. If parts need to be exchanged on a single part basis, the effort is even more reasonable. Nevertheless, for some processes and parts (like injectors, turbine blades or connecting rods) the characteristics of manufacturing lead to variances in critical measures. To overcome this restriction in assembly, selected parts are matched individually.

Additionally, the effort to reach fully exchangeable products in micro manufacturing, dealing with parts of less than 1 mm in at least two dimensions, is high [1]. This is a result of both size effects [2] and small tolerances [3], which have to be taken into account. Micro parts in general will not be exchanged individually, but instead as an assembly. As micro parts are usually exchanged as assembly, after the use phase, the need for exchangeability can be neglected. If there was a method to match parts efficiently, the effort to keep the process within tight limits could be reduced.

2. Selective assembly

Various approaches for selective assembly and matching of parts are well-known from micro, meso and macro level. Kumar and Kannan [4] use genetic algorithms to obtain an optimal manufacturing tolerance for selective assembly. Asha et al. [5] use genetic algorithms to address multiple characteristics. Raj et al. [6] present an approach considering small and medium sized batches for reducing surplus parts with a non-dominated sorting genetic algorithm. Kannan et al. [7] use genetic algorithms for selective assembly and combine Taguchi's loss function for the economic aspect. Process and performance optimization using the Hungarian method for assembly of battery electrodes is introduced by Schmitt et al. [8].

Other approaches use real-time process observation. Colledani et al. [9] introduce a modelling system for the design of selective and adaptive assembly systems. Lanza et al. [10] describe an algorithm for real-time optimization while matching individual components based on their specific measurements.

The utilization of well-known variances in production for adapting tolerances has also been investigated in macro range. For large-volume products like aircrafts, Ballu et al. introduce an approach that allows a progressive modelling of features, parameters and tolerances within the design stage [11]. Anwer et al. use Skin Model Shapes for reflecting shape deviations and supporting tolerance management [12].

All of these approaches are dealing with parts, which can be handled and matched individually. For micro manufacturing, parts are combined in long sequences and are linked physically. The linkage between linked micro parts assures the retention of parts in the right order. For this reason, only approaches that consider linkages between data points are applicable. Conventional selective assembly approaches consider the data points independently of their order. For this reason, these approaches cannot be used. A methodology that does not alter the order of data points in a set sequence is required.

3. Micro mass matching

Micro manufacturing uses linkages to overcome size effects, alter handling and sorting processes for enabling mass production

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[13]. The design of the linkage is divided into ladder type, line type, and comb type [14]. Long-term storing and provision of linkages is e.g. done by winding [15]. Hence, linkages can be maintained till assembly. The product quality is assured as long as all parts in the linkage are fully exchangeable. Production processes are therefore kept in tight limits, while deviations interrupt the process. For most micro assemblies, only a few measures have to be considered in tight tolerances. Especially those measures, where assemblies are connected with each other are important. Within the assembly, measures need to be kept within a certain tolerance in combination with each other. The consideration of the tolerances for two parts moves the tolerating from part to assembly group.

Knowing the characteristic degradation curve, trends for the increasing deviation from the nominal value can be identified [16] and sequences from the linked parts can be derived. Each sequence of linked parts stays in a certain, defined value range. Identified matching sections can be provided for assembly, which individually would not be within the tolerances for exchangeable parts, but fit within the tolerance for assembly.

As trends cannot be expected to run in parallel lines for different values nor, to be steady throughout production, trends from production need to be evaluated and clustered. Thereby the trends could be taken back to design stage in order to adjust the nominal value and allow the maximum matchings from a certain combination of parts and processes [13].

From a technological point of view, matching specific clusters within the linkages need specific conveyance technique as proposed in [17], where parts are sorted and prepared in pacing frequencies of up to 400 parts per minute.

The concept of tolerance field widening and synchronisation of processes is depicted in Fig. 1, using the example of cups and spheres, that are produced as ladder type (cups) and line type (spheres). Spheres and cups are parts that could be manufactured in high rates by micro cold forming. Between these steps, a buffering is required due to different process times. In order to understand deviations and trends in the processes, in the first step every cup and sphere is measured. The critical measure is the relation of the inner diameter of the cup d_c and the diameter of the sphere d_s. To widen the allowed production array, trends need to be derived. In the second step, the tolerance field widening, these trends can be identified by clustering. Clusters will be matched afterwards by considering the fit size for maximizing the output of assemblies. Beyond that, the knowledge of the existent trends of the measured diameters $d(t)$ could be utilized. Therefore, the trends are adjusted by adding or subtracting an identified value for further improvements. This step is repeated iteratively and proven by another matching. The produced parts are stored on coils and in the third step; the parts are assembled according to the results of the tolerance field widening. The required fast and precise conveyance, as well as the output improvements by widening of the tolerance field, interdepends. To achieve high throughput rates, there should be a low number of cuts within the linked parts for minimizing interruptions while production [13]. According to the measured diameters of these parts and their deviation from the tolerance zones, e.g. due to occurring wear, preferably long sections are required. This assures a fast mass production, while widening the tolerance field. The identification of sections with similar trends facilitates long sections for assembly.

4. Cluster algorithms

Cluster algorithms are used to identify groups of data points that are homogeneous within the cluster and are heterogeneous to data points of other clusters [18]. These algorithms are often tailor-made for specific uses. Algorithms for identifying trend-specific clusters must meet the following use case specific requirement of considering linkages between micro parts.

According to graph theory, the parts could be considered as nodes and the linkages as edges between these data points. For this reason, cluster algorithms for networks must be applied. Schaeffer divides the procedure of building clusters in networks into two approaches [19]. The first one is using the edges (linkages of data points) for identifying intensively connected communities of data points as clusters. The second uses similarities of data points [19]. Within the first approach, density-based key figures are used that are non-applicable for identifying trend-specific clusters. These key figures like the density on its self are based on the interconnectedness of data points [20]. Looking at linked parts, the linkage between the data points is equal; every part has one predecessor and one successor. For this reason, only the second field of algorithms that bases on similarities is applicable. Similarities according to connectivity of data points for identification of highly connected subgraphs [21] are also not applicable. The application of distances as similarity measure is one further possibility [22]. For considering trends, the changing of the data points must be taken into account in both kinds of linked parts. While looking at the example of cups and spheres, the diameter is crucial for building functional assemblies. In Fig. 2 the order of parts is depicted exemplarily for spheres. For identifying trends, the distance between diameters of sphere i (d_{Si}) and sphere $i + 1$, and therefore the distance of diameters between sphere $i + 1$ and sphere $i + 2$ of the linked parts is significant.

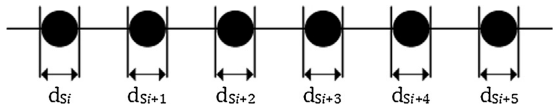

Fig. 2. Order and diameter of line linked parts as basis for clustering.

Similar distances between spheres and cups could be interpreted as similar trends. The Euclidian Distance [22] is used as a similarity key figure and ensures numerical stability. The Euclidian distance of the diameters of part i and the diameter of the part $i + 1$ $\mathrm{Dist}(d_{Pi}, d_{Pi+1})$ is calculated as:

$$\mathrm{Dist}(d_{Pi}, d_{Pi+1}) = |d_{Pi} - d_{Pi+1}| \tag{1}$$

Clustering algorithms can be divided in several approaches that differ in their procedural method. Hierarchical cluster algorithms are dividing or adding data to clusters corresponding depicting hierarchical structures [19]. The methodology of building clusters is more useful than dividing, since agglomerative hierarchical algorithms are starting at considering every data point as a single cluster and then building clusters until a stop criterion is reached like e.g. the number of clusters. When forming clusters by divisive hierarchical cluster algorithms, cluster fitness functions homogeneity of data or the density within clusters is considered. These approaches do not facilitate the identification of trends.

While identifying trend-specific clusters, the number of clusters and sizes of clusters should not be defined. The pre-setting of a

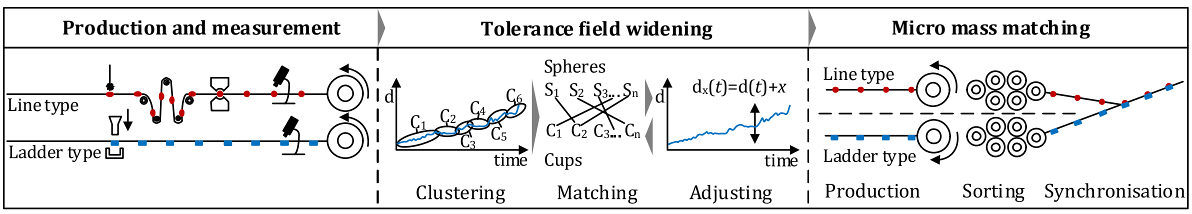

Fig. 1. Concept of mass matching of micro parts.

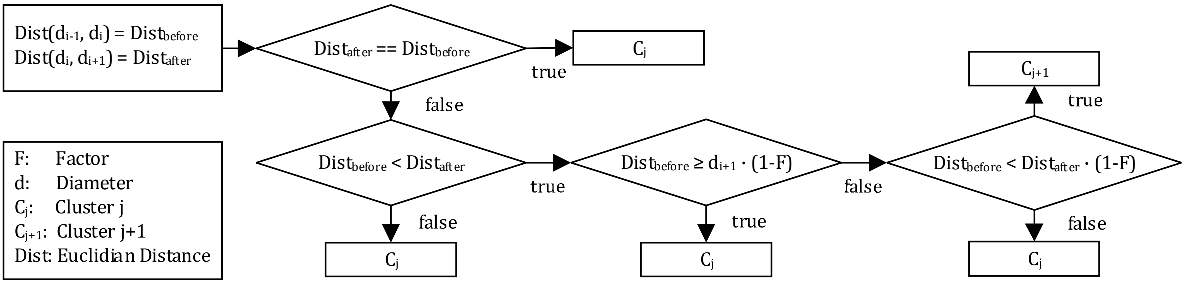

Fig. 3. Linked Parts Clustering Algorithm.

defined number can impede the identification of trends. Looking at the example of cups and spheres, there are two measured data sets that must be clustered.

5. Linked Parts Clustering

Most of the existing agglomerative hierarchical cluster algorithms for networks, like the well-known Clique Percolation Method [23], the Concept of Brightness [24] or Hierarchical Link-Clustering [25], consider density measures for building clusters. The Linked Parts Clustering (LPC) is a non-iterative algorithm that is based on the schematic approach that is depicted in Fig. 3. The LPC clusters the data points according to their order so that the original sequence of data points is preserved.

The Euclidian Distance is used for calculating the distance before d_{i-1} and after d_{i+1} a data point i. the data point is added to the actual cluster c_j or a new cluster c_{j+1} is started. A data point can only be added to a new started cluster or the previous one. Since in manufacturing processes variances occur, there are thresholds required for decreasing and avoiding the influences of variances while building clusters. For this reason, the assigning clustering factors F_1 or F_2 are used. The multiplication with F_1 and F_2 delivers these thresholds and avoids a building of a high number of very small clusters. In case of unequal upper of lower limits of the variances F_1 and F_2 must be different, otherwise the tolerances are the same.

6. Experimental set up

Benchmarking of cluster algorithms is often done comparing two or more algorithms [21]. For this reason, the introduced methodology for clustering of trends is evaluated using the following experimental set up. The following data with changing trends were defined to evaluate the LPC and selection of parameters. Two sets of data, each with 2000 data points, bearing changing linear trends were simulated considering the parameters that are listed in Table 1. Data set 1 simulates a slowly increasing diameter of cups starting at 891.84 μm, and data set 2 simulates a faster decreasing diameter of the spheres that starts at 909.16 μm.

For investigating, how the identification of trends and the determination of tolerances for thresholds is influenced by occurring variances, randomized data is used. Randomization is done by adding a uniform distributed numbers on the diameter. The upper and lower limit of these data is listed in Table 2. The simulated values are added or subtracted from the data of the simulated trend.

For the simulated data, the changes within the trends and the variances are defined. Therefore, it is possible to evaluate if the LPC identifies trend-specific sections and how the defined assigning clustering factors F_1 and F_2 must be chosen in dependence to the variances. Due to the upper and lower limits of the variances in Table 2 there is no differentiation between factor F_1 and F_2 necessary. The introduced clustering algorithm for linked parts was implemented using Python 3.4.4.

For both data sets, the three scenarios of variances were tested with variable assigning clustering factor F. Starting at a factor of 0.5 the factor was changed in steps of 0.05. Depending on the number of clusters, it was decreased or increased until trend changes were identified. For evaluating if the LPC algorithm identified the trends successfully, data sets are used, where the trends and clusters are well known.

Table 1
Parameters for simulating varying trends.

	Trend	Rise/fall	Up to
Low trends	01	−0.0011	750 parts
	02	−0.0012	1200 parts
	03	−0.0015	1500 parts
	04	−0.0016	1900 parts
	05	−0.0017	2000 parts
High trends	06	+0.001	1000 parts
	07	+0.002	1500 parts
	08	+0.003	1700 parts
	09	+0.004	1800 parts
	10	+0.005	2000 parts

Table 2
Simulated variances.

Scenario	1	2	3
Upper limit [μm]	+0.001	+0.005	+0.009
Lower limit [μm]	−0.001	−0.005	−0.009

For both data sets, the three scenarios of variances were tested with variable assigning clustering factor F. Starting at a factor of 0.5 the factor was changed in steps of 0.05. Depending on the number of clusters, it was decreased or increased until trend changes were identified. For evaluating if the LPC algorithm identified the trends successfully, data sets are used, where the trends and clusters are well known.

7. Experimental results

The results show that the LPC identifies trend-changes. In all scenarios, an increasing factor F leads to a decreasing number of clusters, since the annexation to another cluster is avoided.

For the data set with high changes of trends in the first scenario, the algorithm identifies the number of clusters and the cluster boundaries are covering the simulated trend changes as depicted in Fig. 4.

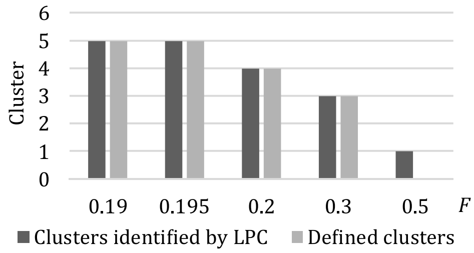

Fig. 4. Identified clusters of high trends in scenario 1.

Within the second scenario of variances all clusters of the data set with high trends have been identified again as depicted in Fig. 5. The assigning clustering factor *F* does not change for these two scenarios even if the variances are four times higher. Again, all identified cluster boundaries coincide with the simulated trend changes.

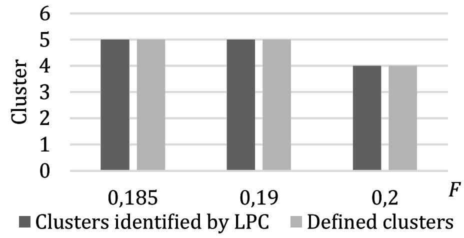

Fig. 5. Identified clusters of high trends in scenario 2.

Within the third scenario of high trends, there are only a few cluster boundaries correctly identified even if a higher number of clusters is recognized. The maximum number of right identified trend changes is depicted in Fig. 6 In accordance to the higher variances the explanation is that the identified changes are boosted randomly by the variances.

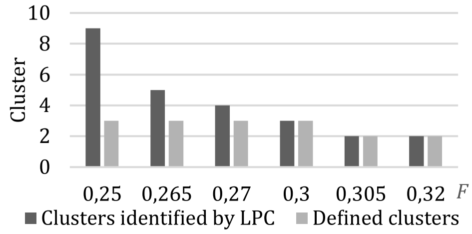

Fig. 6. Identified clusters of high trends in scenario 3.

The data set with the lower trend changes shows that in this case the influence of the variances is so high that the trend changes were not identified as depicted in Fig. 7. Even in higher number of clusters the boundaries do not match simulated trend changes.

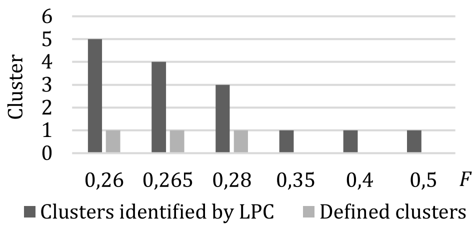

Fig. 7. Identified clusters of low trends in scenario 1.

8. Summary and outlook

Micro mass matching offers opportunities for micro production to invert the idea of tight tolerances and process arrays, and allows a higher utilization of tools and hence higher output. Basis for the approach is the ability to automatically analyse critical measures and identify trends and clusters. The LPC algorithm presented here shows the ability to identify trends within production data and define trend specific clusters, as long as the statistical variance of the data is not exceeding trend effects.

The two parameter sets indicate that a sole consideration of the two next neighbours of these data points is only applicable if the variance is not exceeding occurring trends. The introduced methodology is a basic course of action that has to be investigated in further studies to further reducing the intensity of the trend and also considering real data with mixed trend characteristics. Furthermore, it should be investigated if the flexibility of the matching process could be supported with overlapping of clusters. For assuring flexibility while matching of clusters according to their fit size, it is necessary that the algorithm enables overlapping clusters. Thereby, changing sizes of clusters could be balanced since possible sections that are usable for two clusters are already identified.

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