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Statistics-based Quality Control of Patterns

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Abstract. This study addresses a statistics-based testing procedure aimed at optimizing quality assurance for custom-made and made-to-measure (CM/M2M) clothing patterns. The procedure focuses on identifying machine-detectable issues in patterns before they progress to the expensive and time-intensive manual tailoring phase, thereby streamlining the testing cycle and reducing both time and costs. By analysing patterns for individuals with similar body measurements and applying statistical methods, the study identified potential design errors in pattern pieces based on measurable properties such as perimeters, areas, and contour-defining lines. Advanced statistical techniques, including residual analysis, Cook's distance, and Mahalanobis distance, were employed to detect outliers and pinpoint potential construction errors. Further analysis of line properties using predictive models—such as linear regression, random forests, generalized additive models (GAM), and rpart decision trees—revealed that a high frequency of outliers often correlates with construction anomalies. This research demonstrates that predictive modelling and outlier detection are effective tools for identifying errors in CM/M2M pattern construction, contributing to improved garment accuracy and production efficiency.

Keywords: Custom-made Clothing, Made-to-measure, Garment accuracy, Statistical testing, Outlier detection, Predictive modelling

1. Introduction

Personalized or custom-tailored clothing patterns are created in various contexts — both in traditional custom clothing production (the atelier model, where individual measurements are taken from the client and the garment is constructed according to these specific measurements), as well as in fashion houses (for small-scale clothing collections and individually crafted, high-quality designer garments). Additionally, specialized companies offer clients the option to purchase custom-designed patterns, often in digital formats.

According to a 2024 report (Sneha, 2024) by *Cognitive Market Research*, the global market for custom-tailored clothing was valued at approximately $50 billion, with a projected average annual growth rate (CAGR) of 10%. Researchers believe that, with the rise in digital accessibility, industrially manufactured custom-sized garments will gradually replace the current dominance of mass-produced standard-size clothing. This shift will significantly alter consumer purchasing habits, clothing production methods, and associated global supply chains. People will no longer need to buy off-the-rack clothing that only partially meets their preferences or fits their body size; instead, they will be able to order any desired garment (in a design of their choice, possibly even self-designed) tailored precisely to their measurements and delivered directly from the manufacturer.

The primary challenge in advancing the custom-made/made-to-measure (CM/M2M) clothing segment (McKee, 2024) lies in the objective difficulty of ensuring that garments sewn from automatically generated (algorithm-based) clothing patterns really fit the individuals for whom they are intended. In traditional custom tailoring, fit verification occurs manually — the garment is created, tried on by the wearer, and then altered (sometimes in multiple iterations) until it fits perfectly. However, if a pattern is generated automatically for a person located at a geographical distance, the fitting and alteration phase becomes not only costly (fabric, time) but may also be impractical (if the person is unavailable for fittings).

A solution must be found to ensure that the algorithm used to generate custom clothing patterns can, with a high probability, produce a pattern that fits well. Complete verification of the algorithm's accuracy could theoretically be achieved by sewing a garment for every person on Earth, but this is, of course, an unrealistic task.

The study describes how to accelerate the testing/improvement cycle for creating personalized products (clothing patterns). In today's fashion industry, developing such products involves a highly manual and iterative quality improvement process (sewing/fitting). The testing method described in the study, which is based on statistical methods, has the potential to speed up and thereby reduce the cost of the testing/improvement cycle for such products, as it allows manual fitting to be deferred until automatically identifiable issues have already been resolved.

The statistical methods described in the study can utilize variables that are either already available or can be easily obtained during the product construction process. The study concludes that, in practical application, the number of indicators to be tested will be significant and that these must be interpretable within the context of their application. Therefore, the main challenge of the outlined testing method is to quickly identify and exclude from further testing those indicators that are not useful for identifying issues in the tested pattern within the context of statistical methods.

The variables used in this testing method can be applied with any personalized garment construction system that produces results in vector graphics form. The description and its implementation can also be adapted for other CAD systems that create two-dimensional construction images from interrelated input data.

1.1. Problem Identification

Compared to a typical situation in software testing, quality assurance of a CM/M2M product under development faces several specific challenges — both in terms of input data and in evaluating the results achieved.

The input data for CM/M2M products (garments) consists of body measurements of individuals to be clothed where some of these measurements might be specific to the construction method used. Since a CM/M2M product is generally developed with the intent to be suitable for a large part of the population (e.g. all adult women), there is a need to provide data that covers the potential market of the product's potential buyers regarding the relevant body measurements.

Regardless of whether the CM/M2M product is offered to the customer as a finished garment or merely as a CM/M2M pattern, its quality is ultimately assessed by how well the resulting garment fits the individual. In addition to the physical process of tailoring/fitting, there should also be considered that the quality of fit is only partially quantifiable.

We will discuss these specific aspects of quality assurance for CM/M2M products in detail in the following sections and derive an accelerated quality assurance procedure from this analysis.

1.2. Main Idea of Solution

The procedure presented in the study aims to detect machine-identifiable issues within the CM/M2M product before the costly tailoring/fitting process begins. The concept is based on the assumption that the CM/M2M patterns for two individuals with similar body measurements must also be similar. Assuming it's possible to generate automated quality measurement indicators of "similar" or "different" for patterns, statistical methods are then used to identify test cases that deviate from the expected results.

Although this approach would not allow for assessing the overall quality of the pattern in terms of fitting, it holds significant potential to speed up the testing/improvement cycle for CM/M2M products. This approach would postpone the expensive and entirely manual fitting checks until after addressing the more apparent quality and measurement data issues in the patterns, which can be identified automatically.

2. Quality Control of Patterns

2.1. CM/M2M patterns used in the study

The procedure for statistics-based, automated problem identification presented in this study (hereafter referred to as the Testing procedure) is derived step by step. Initially, the simplest possible variant is applied to a straightforward yet practically relevant example: a basic skirt pattern. Even from this simple application, prerequisites for the use of statistical methods in quality assurance can be deduced.

While the first application case utilizes only two characteristics that define the size of the patterns, the second application case, involving the basic bodice pattern, also takes the shape of the patterns into account, significantly increasing the number of characteristics considered.

To avoid the implicit dependency of the Testing procedure on the construction method used by the authors for pattern creation, the procedure is also applied to similar patterns from a publicly available CM/M2M product study (Harwood et al., 2020), specifically the basic skirt pattern and the basic sweatshirt pattern (including two sleeve variations) provided with this solution. For this purpose, the .dxf files generated by this system were first converted into .svg files; the details of this process can be found in (Neimanis et al., 2025) – refer dxftosvgconverter.zip.

All the aforementioned examples used in this study are base constructions (patterns that serve as base to develop more complex garments) consisting only of one or few pattern pieces. They were selected with the goal to derive the Testing procedure but not to overload it. The practical application of the Testing procedure in real-life CM/M2M product development is foreseen in upcoming research.

2.2. Input Data used for the study

In the development of CM/M2M products, body measurements pertaining to the person to be clothed serve as input data. Unfortunately, CM/M2M products lack a standardized system for determining body measurements — each manufacturer uses its own, distinct set of measurements and interpretations (Januszkiewicz, 2021).

However, we can reasonably assume that each CM/M2M product manufacturer has access to their own set of body measurement data and is aware of the quality of their test data. Furthermore, it can be assumed that they are able to obtain measurement data from new individuals involved in the process (for example, new clients purchasing patterns or ordering custom garments online).

In another study (Bicevskis et al., 2024), the authors of this study analyzed the possibilities to extract test data from CM/M2M product development data. As result of that study a test database with 469 female body profiles was accessible, each profile having 37 measurements. As discussed in details of that study the data covers a wide range of female body types, but the quality of that data is not homogenous. In Section 2.4, we will demonstrate what impact low-quality input data can have on the Testing procedure described here.

In order to use the second CM/M2M pattern-generating system (Harwood et al., 2020) discussed above (refer Section 2.1), some of the measurement data had to been transferred matching the definitions of that second system.

2.3. Determining the Quality of Patterns

Determining the quality of patterns as a product is quite complicated at its core, as this intermediate product's quality can ultimately only be assessed by a person after trying on the clothing made from the pattern (a person visually confirms whether the garment fits the specific individual or not). Therefore, the quality of the pattern can only be partially determined by quantitatively expressible and measurable indicators, and subjective factors play a significant role.

Garment fitting has been extensively studied, analyzing both its subjective factors (Fan et al., 2004), (Hernández, 2018), (Zhang et al., 2011), (Brownbridge et al., 2013) and attempting to create objectively verifiable criteria (Sayem et al., 2017). Although there have been initial steps toward the digitalization of fitting (WEB (a) (WEB (b)), (WEB (c)), there is currently no convincing alternative to the iterative sew/fit approach (Keefe et al., 2017), (Lagė et al., 2020), which is a significant barrier to the development of CM/M2M products (new clothing models) and a crucial cost factor in the overall development of such clothing design products.

The decision that a garment is "sufficiently well-fitting" is made during a fitting process conducted by a person, often under variable conditions (such as the fabric used, lighting, available time, etc.). Even if the "sufficiently well-fitting" decision is made by a qualified specialist, it will never be entirely free of subjectivity. Given this subjectivity in fitting practices, there has yet to be a universally adopted, quantitatively expressible, and practically measurable indicator that could serve as the basis for making a "sufficiently well-fitting" decision.

Attempts have been made to overcome subjective factors and evaluate quality with quantitative indicators (De Silva et al., 2024), (Wang et al., 2006), for example, by determining the pressure exerted by the garment or measuring the space between the body and the garment. However, the practical application of these indicators is challenging — their assessment cannot be conducted without additional labor and/or technical equipment.

In the absence of digital alternatives, it is advisable to apply the manual, costly tailoring/fitting process only after automatically detectable issues have been resolved. In the following, we will demonstrate how it is possible to identify potential construction deficiencies in the CM/M2M product using purely computer-based methods by analyzing the properties of the generated patterns.

2.4. Fault Diagnosis on Piece Level

To identify potential design errors based on the created patterns, it is first necessary to express the dissimilarity of two patterns generated for two individuals.

Since, in a computer-aided process, we are naturally unable to apply the subjective criteria discussed in Section 2.3, we require quantitatively expressible comparison metrics.

Viewing patterns as sets of two-dimensional images makes comparing them a complex task. It is immediately clear that this comparison problem can be reduced to examining each pattern piece individually.

Figure 1. Samples of pattern pieces and their outer contours

From a purely mathematical perspective, there exist numerous methods to compare two graphics in a two-dimensional space; however, we will limit ourselves to those that are both professionally justifiable and practically computable.

Each piece, in the context that interests us in terms of its relevance and applicability from a professional perspective, consists of a line describing its outer contour, which represents the boundary of the fabric to be cut. The other lines and symbols visible in the pattern image merely provide supplementary information for the pattern user and are irrelevant in this context.

Defining the notion of "identical" in terms of pattern use as an abstraction for cut fabric is straightforward: two patterns are identical if the shape and size of their outer contour lines are the same.

Note: By default, we assume that the orientation of comparable pieces on the fabric (i.e., the grainline direction) will always be the same across different input data sets, meaning that comparable pieces will not be rotated.

However, if we want to determine how "different" two pieces are, we quickly realize that quantifying their difference with a single number is not feasible. Even a simple piece like a rectangular belt demonstrates this; the shape and size of the belt can only be described using at least two numbers (e.g., length and width). This simple rectangular example highlights that it's impossible to define a single universally applicable value to characterize the difference between two pattern pieces. Therefore, we will examine differences based on various indicators, guided by both the application context and the practical consideration that these indicators must also be computable.

When searching for parameters that can characterize a piece, we intuitively consider its Perimeter (the length of the outer contour) and the Area (surface) it encompasses. These two parameters are advantageous, both because they are clearly suitable in this context (as the size of a person increases, more fabric is required, leading to larger Perimeters and Areas) and because they can be easily obtained — either directly from the CM/M2M pattern-generating system or, in any case, from vector data found in the file representing the pattern.

This leads to the following research question:

Research question 1: How and under which requirements potential errors in the construction of a CM/M2M pattern can be identified using quantitatively measurable properties of pattern pieces?

To initially focus on the approach, we chose a pattern-making program of medium complexity (base pattern for skirts) as the first application example, whose quality is good based on practical experience. The same data, which was already used in the validation of input data (refer section 2.2), was used as input data here. Thus, patterns were generated for 469 datasets of different quality, and the length of the Perimeter and the Area for the two pieces FRONT and BACK were calculated.

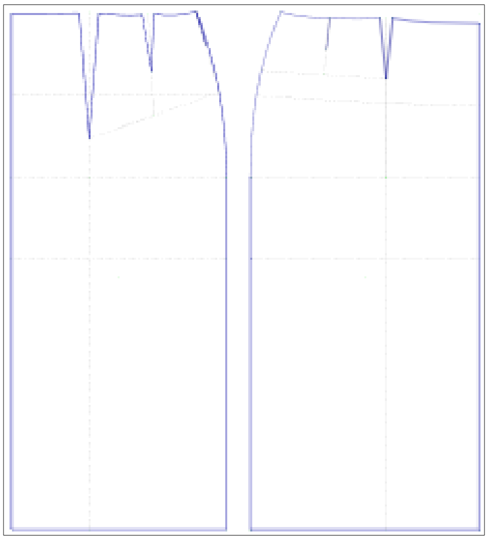

Figure 2. Base skirt pattern sample

The results were analyzed using the statistical programming language R (R Core Team, 2024). It was calculated how much the Perimeter and Area of each piece correlate with the measurements used to generate them. The Area showed a higher correlation than the Perimeter. The Pearson correlation coefficient (R Core Team, 2024) for the BACK piece Area was 0.955, while for the FRONT piece it was 0.956. Lower results were found for the correlation of measurements with the Perimeter of the pieces: FRONT - 0.614, BACK – 0.865.

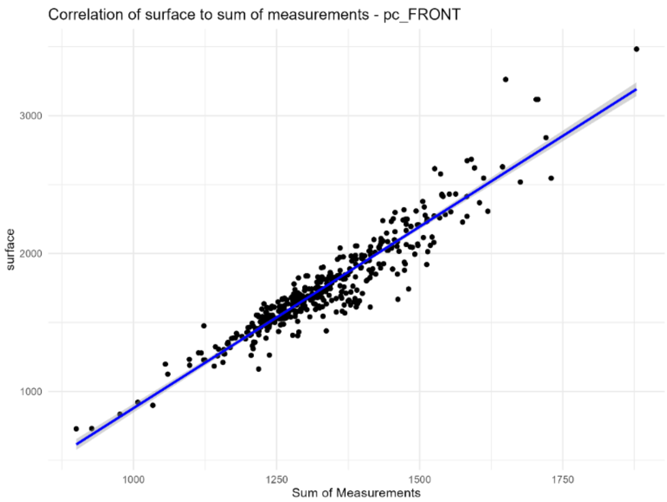

Figure 3. Correlation of the Area of the skirt's piece FRONT with the measurements

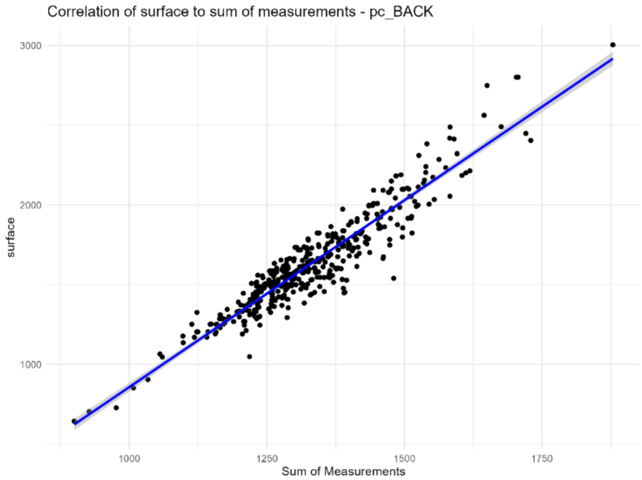

Figure 4. Correlation of the Area of the skirt's piece BACK with the measurements

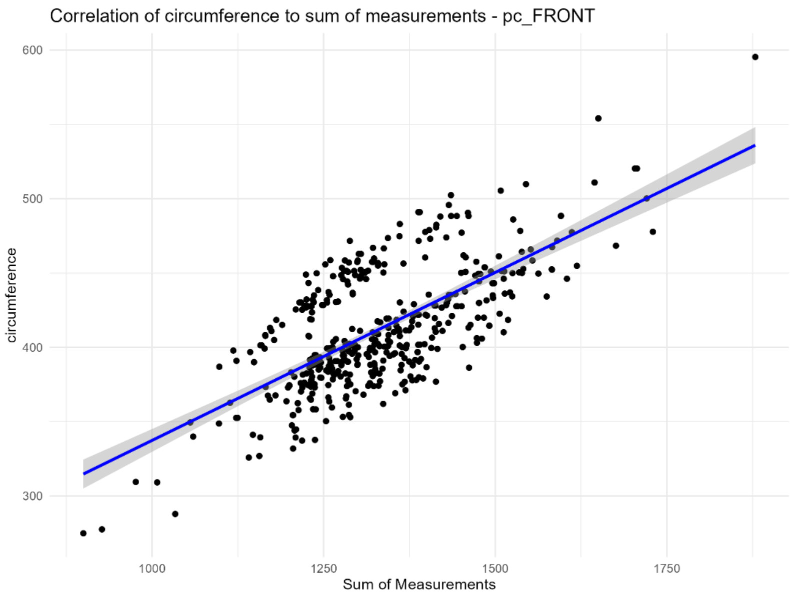

Figure 5. Correlation of the Perimeter of the skirt's piece FRONT with the measurements

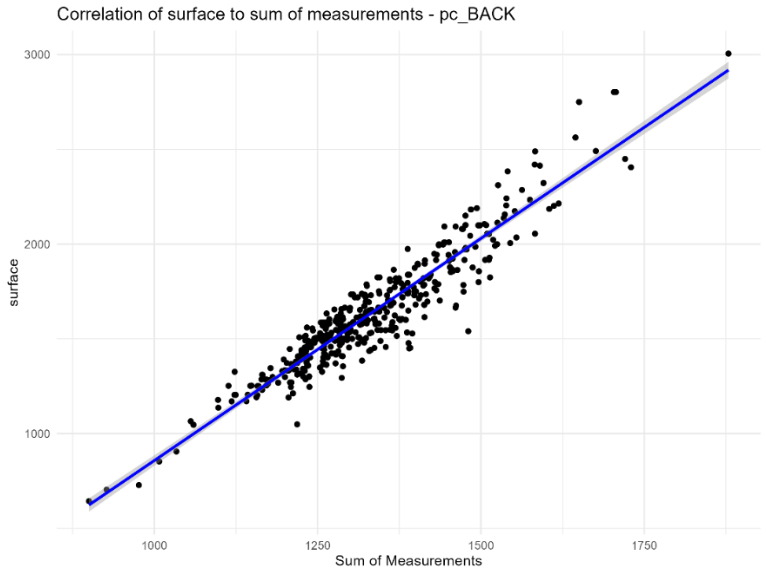

Figure 6. Correlation of the Perimeter of the skirt's piece BACK with the measurements

A statistical model was repeatedly created and trained for each piece and dependent variable (Perimeter or Area).

Initially using a linear regression approach (the lm() function (R Core Team, 2024)), followed by use of predictive models with resampling and hyperparameter tuning (the train() function (Kuhn, 2008)) the predicted results were compared with the actual ones and iteratively improved.

The summary indicators of each model (Residual Standard Error, Coefficient of Variation, R², Adjusted R², F-statistic, p-value) were also recorded, and the maximum, minimum, and average deviations from the regression line were calculated.

piece	group	Residual_Standard_	Coefficient_of_Variation	R_squared	Adjusted_R_squared	F_statistic	p_value
pc_BACK	surface	49.26 ↓	**3.0%** ↓	0.98 ↑	0.97 ↑	1945.64 ↓	0E+00 ↓
pc_FRONT	surface	52.20 ↓	**3.0%** ↓	0.98 ↑	0.98 ↑	2202.00 ↓	0E+00 ↓
pc_BACK	circumference	5.90 ↓	**2.7%** ↓	0.91 ↑	0.90 ↑	472.09 ↓	5E-221 ↓
pc_FRONT	circumference	8.95 ↓	**4.4%** ↓	0.79 ↑	0.79 ↑	185.58 ↓	2E-144 ↓

Figure 7. Main statistical indicators of the Area and Perimeter regression models for the FRONT and BACK pieces

piece	group	min	median	mean	max	min_perc	median_perc	mean_perc	max_perc	lower_bound_16	upper_bound_84	lower_bound	upper_bound
pc_BACK	surface	**-203.94** ↑	1.94 ↓	-5E-13 ↑	**143.90** ↓	**-23.82%** ↓	0.15% ↓	0.00% ↓	**9.22%** ↓	-42.79 ↑	47.57 ↓	-114.19 ↑	78.26 ↓
pc_FRONT	surface	**-254.56** ↑	1.38 ↑	8E-13 ↑	**130.95** ↓	**-30.71%** ↓	0.08% ↑	-0.04% ↓	**7.11%** ↓	-41.69 ↑	47.91 ↓	-110.74 ↑	94.77 ↓
pc_BACK	circumference	**-28.88** ↑	0.49 ↑	-7E-14 ↑	**15.10** ↓	**-11.71%** ↓	0.21% ↑	0.06% ↓	**7.24%** ↓	-3.39 ↑	4.63 ↓	-17.19 ↓	10.09 ↓
pc_FRONT	circumference	**-22.12** ↑	1.99 ↓	-1E-13 ↑	**16.20** ↓	**-9.44%** ↑	1.03% ↓	0.18% ↓	**8.73%** ↓	-11.22 ↑	8.87 ↓	-17.63 ↑	13.09 ↓

Figure 8. Deviation indicators from Area and Perimeter regression lines for the FRONT and BACK pieces

The finally reached indicators are visible in the above table *(Remark: the red and green arrow icons indicate the model's performance compared to the previous iteration)*. The according R script is available in (Neimanis et al., 2025) – refer R scripts.zip.

Various approaches to identifying outliers were tested:

(i) **Residuals** (WEB (d)) – differences between predicted and observed values. The highest 2% were marked as outliers. The results were visualized with a **Q-Q plot**(Wilk and Gnanadesikan, 1968), and points (profiles) far from the blue line can be considered outliers.

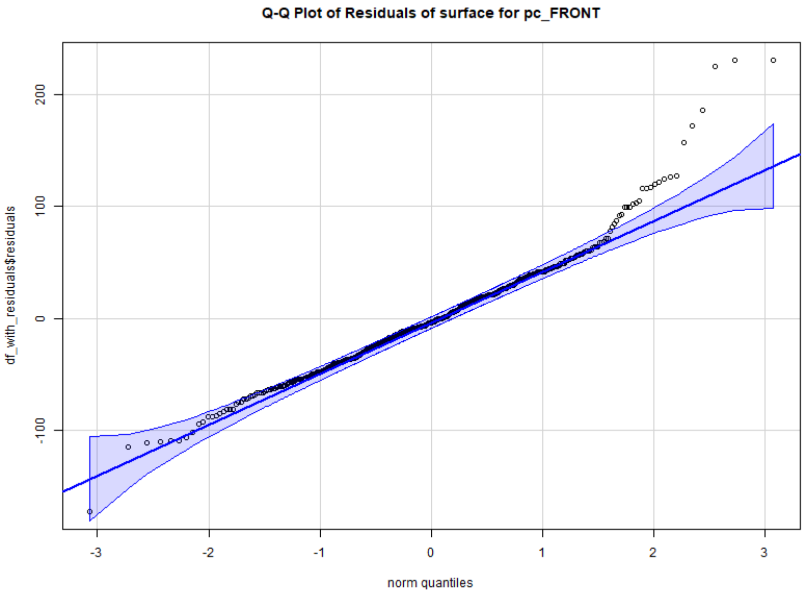

Figure 9. Visualization of the residuals
for the Area of FRONT piece with a Q-Q plot

(ii) **Cook's distance**(Cook, 1977) - helps to identify data points that could significantly influence the results of the regression model. Outliers are determined using the formula 4 / (n - k - 1), where the number 4 is used as an empirical constant often applied to identify influential data points in a regression model; n is the number of observations in the dataset; k is the number of independent variables in the model (number of regression coefficients excluding the intercept). In this case, data points whose Cook's distance exceeds the calculated threshold value are considered influential. In figure 10, the threshold is illustrated with a red dashed line. There are quite a few outliers but there exist some distinctly influential data points between them.

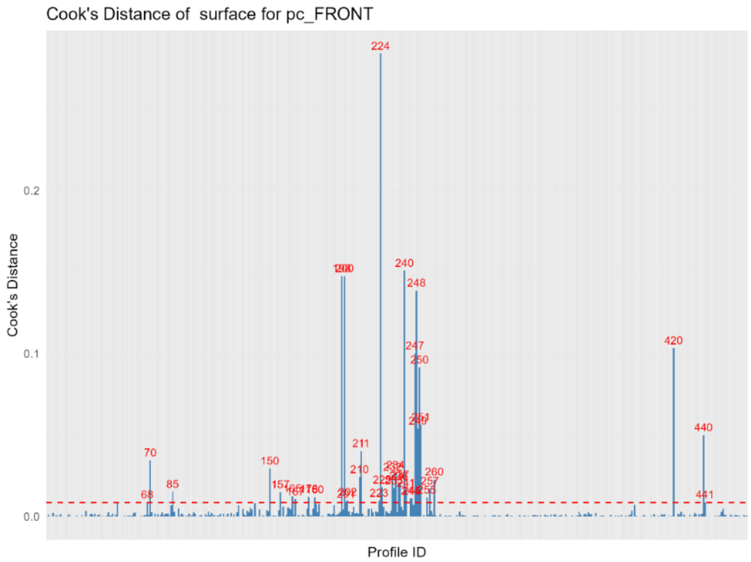

Figure 10. Visualization of Cook's distance for the Area of FRONT piece

(iii) **Mahalanobis distance** (Mahalanobis, 1936) - used to identify outliers in multidimensional data. It is calculated in R using the mahalanobis() function (R Core Team, 2024) which uses data matrix, the mean vector, and the covariance matrix of the residuals. The highest 2% are marked as outliers.

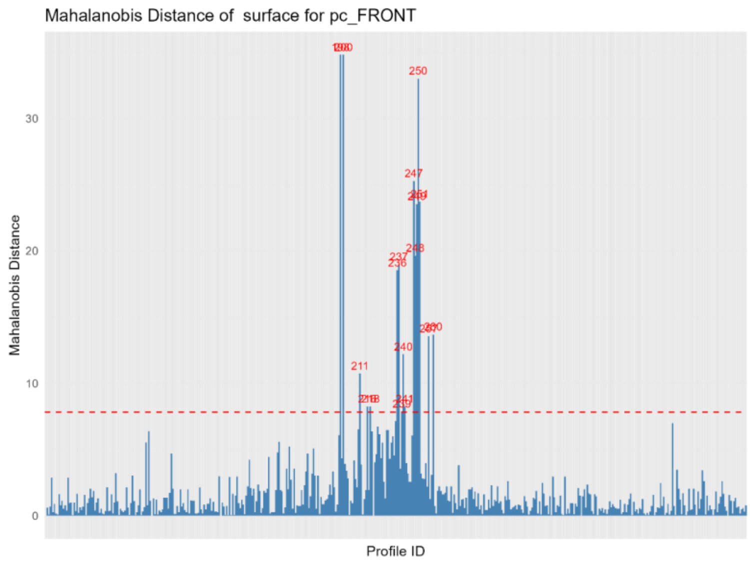

Figure 11. Visualization of Mahalanobis distance for the Area of FRONT piece

Outliers identified by Cook’s and Mahalanobis distances were also recorded in a scatter plot, which visualizes how consistent the data is for training and predicting with the linear regression model.

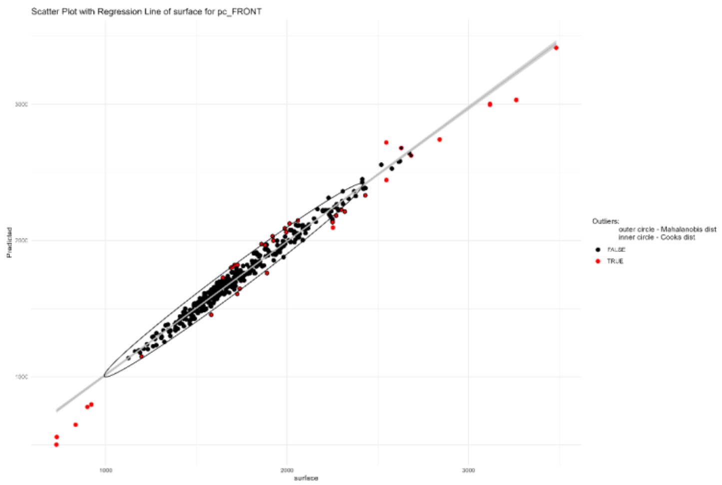

Figure 12. Scatter plot of Cook’s and Mahalanobis distances for the Area of FRONT piece

The output of all outlier detection methods were combined and summarized in EXCEL tables, which are available in (Neimanis et al., 2025) - refer Perimeter and Area attachments.zip.

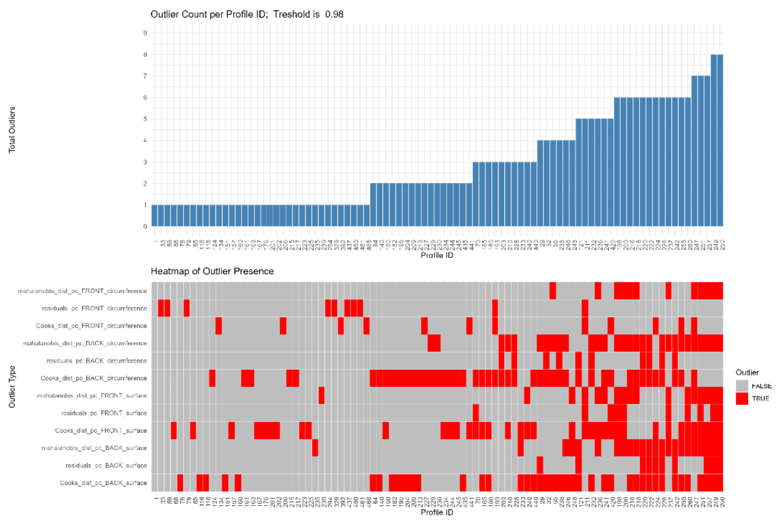

Figure 13. Identified profiles with the highest error probability for the Perimeter and Area of the FRONT piece

2.5. Fault Diagnosis on Line Level

The previously analyzed variables Perimeter and Area can only be used as indicators of large structural deviations, as neither of these quantities considers the possible shape differences of any two pieces. Therefore, in further analyses, we will focus on how to also consider shape.

Research question (2.5): How and under which requirements potential errors in the construction of a CM/M2M pattern can be identified using properties characterizing the pattern pieces' shape?

To identify shape differences, one can leverage the fact that each CM/M2M piece is constructed using specific types of lines. The characteristics of these lines can then be analyzed to detect differences.

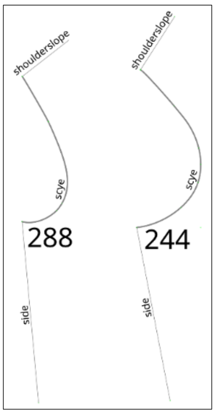

Figure 14. Sample set of comparable lines for patterns of profiles 288 and 244

From a purely mathematical perspective, there are many conceivable variants for defining the indicators used to compare individual lines. However, considering the aspect of applicability, the crucial question becomes how we interpret the location of the line within the common piece. Therefore, we determine that each line's location is characterized relative to the mass center of the respective piece. By aligning the two comparable pieces at their mass centers (without changing their directions defined in the CM/M2M system), we are able to compare the pairs of lines forming the construction of these two pieces.

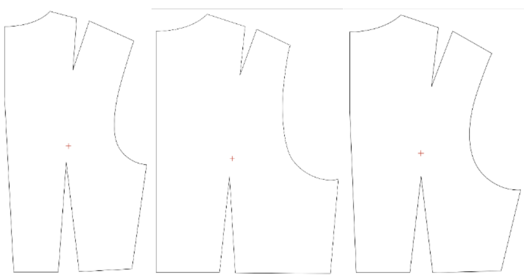

Figure 15. Samples of pieces' mass centers

The following quantities can be used for comparison, all of which (including the required mass centers in this context) are derived from the CM/M2M system or vector data contained in the file representing the pattern:

i. length of the line;
ii. vector (represented as x/y-coordinates) of the starting point from the piece's mass center;
iii. vector (represented as x/y-coordinates) of the endpoint from the piece's mass center;
iv. angle of the line at its starting point;
v. angle of the line at its endpoint.

As an application example for quality analysis using the properties of lines, we use a base bodice construction. This construction, like the base skirt construction used above, has already proven itself in practice. Using the above-mentioned line parameters the quality of a garment construction can be further analyzed applying several statistical methods. To detect potential outliers in the line properties and find out which profile's patterns should be checked for quality control, a similar approach as described earlier in piece analysis (refer section 2.4) was used. First, data was scaled and centered. For each piece, several predictive models were trained using the lines as factors. Several models were applied and the results compared:

- Linear regression (R Core Team, 2024),
- Random forest (Lang et al., 2019), (Wright and Ziegler, 2017),
- GAM (Wood, 2011)
- rpart decision tree (Therneau and Atkinson, 2023).

Their results (using the metrics MAE, MAPE, and R2) were compared to choose the ones with the best performance in each category of predictors:

Model for Length –

type: linear regression model (R Core Team, 2024),

predictors: all measurements used to create the pattern; circumference and surface of the piece where the line is located.

Model for Coordinates –

type: random forest (Lang et al., 2019), (Wright and Ziegler, 2017),

predictors: all measurements used to create the pattern; length of the line.

Model for Angles –

type: rpart decision tree (Therneau and Atkinson, 2023),

predictors: all measurements used to create the pattern; length of the line; start and end coordinates of the line.

These models were used to make predictions on the same data they were trained on, allowing us to compare actual versus predicted values. High differences between these values are candidates for anomalies in the geometry of the lines.

Outliers were detected using Mahalanobis distance and residuals applying the same thresholds as in the piece level analysis (refer Section 2.4) - top 2% of residuals; Mahalanobis distance was assessed using chi-squared distribution (Kahle, 2017), (R Core Team, 2024) to determine if an observation was unusually far from the mean of a distribution.

If the distance or the residual were greater than the threshold the respective outlier was marked. All marked values were summed up for every single line and for every measurement profile. The goal was to detect profiles having the highest outlier count indicating that their measurement data combination has led to some unforeseen geometry.

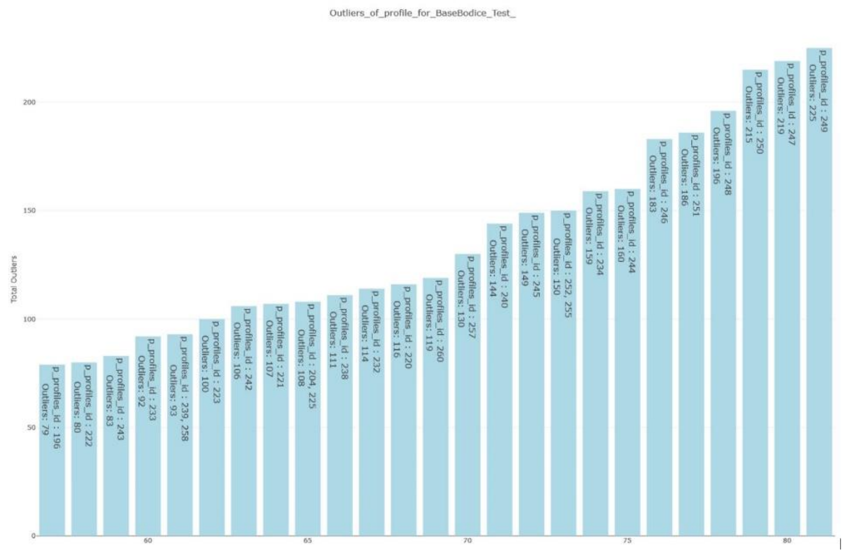

Figure 16. Profiles with highest count of outliers for base bodice pattern

To illustrate the application of such results we can take a closer look onto the profile with the id 249 having the highest number of outliers (225). In the following image of the base bodice pattern for that profile the lines having at least one outlier in one of their parameters are colored red. As a counterpart we added the pattern for the profile with id 254 which has quite similar measurements as profile with id 249 but way less outliers (64).

The comparison between the two patterns illustrates that a high outlier count helps to detect construction anomalies, e.g., the shape of the scye is obviously uneven for profile 249, but smooth for profile 254.

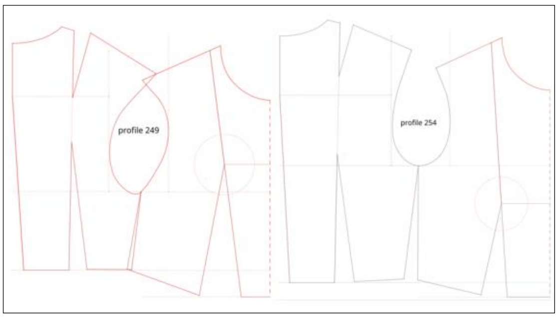

Figure 17. Base bodice patterns for two profiles.

Looking at the list of lines with the highest number of outlier profiles (refer Figure 18), the cl_ScBc line (back scye) appears at the top. This suggests that the scye in the base bodice construction may require improvement.

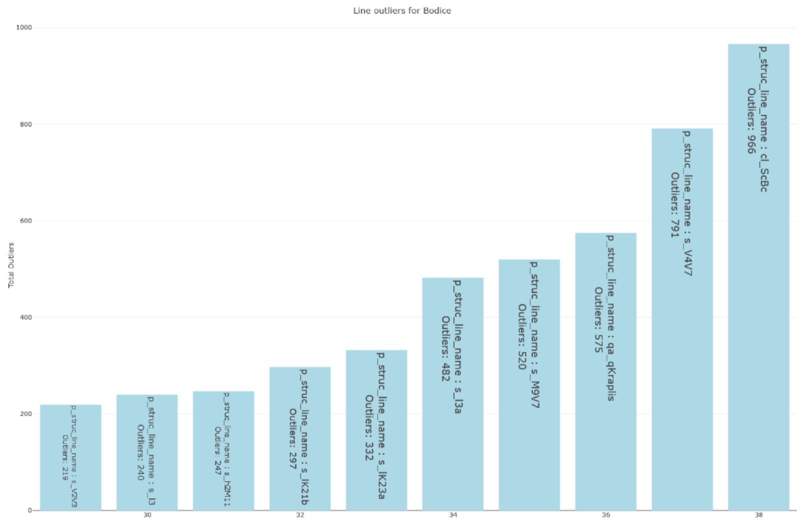

Figure 18. Lines with the highest number of outliers

But it should be considered that scye lines are long and curved. The shape of a scye largely depends on the pattern-making method used to create the bodice, as these methods employ different approaches to combining body measurements. The parameters used so far for the analysis (length, location and angles of start/end) cannot fully characterize the shape of such a line. The two samples from the executed test dataset illustrate that scye lines with nearly identical start/end-angles can have a substantially different form.

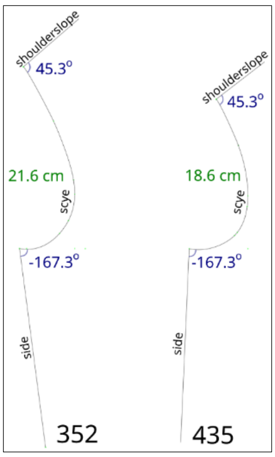

Figure 19. Samples of scye with similar start-/end-angle of profiles 352 and 435

2.6. Fault Diagnosis for .dxf patterns

The samples discussed thus far were created using a CM/M2M construction system that outputs result in a structured format. Every pattern produced by this system comprises the same set of lines arranged in a consistent sequence. Regardless of the profiles for which the program is executed, it generates patterns that are structurally identical. The only specifics are that a line might exist as a 1-point-line (a line having a fixed location but no length). Since that construction method's implementation uses the .svg standard, all these lines can be characterized by a fixed number of parameters, resulting in a structurally fixed set of output parameters The use of statistical methods within the Testing procedure is based on that fixed structure premises.

But not all CM/M2M-construction systems support the .svg standard. Many systems produce their results in other formats, and one of the most popular such standards is .dxf (WEB (e)).

Although .dxf as a standard allows to implement an analogous fixed structure approach, in real life another approach is more popular. That approach is to implement all the pattern's lines as straights connecting many closely placed vertexes as illustrated in the samples below (further on called Vertex-polygon-type).

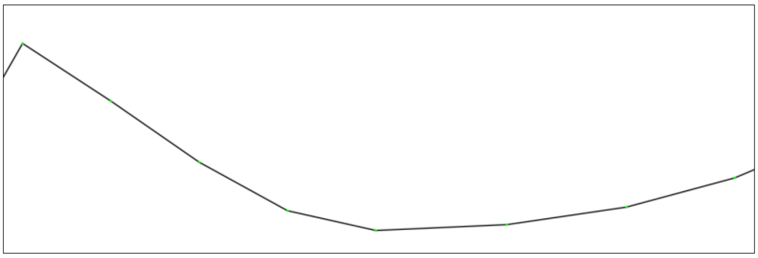

Figure 20. Sample of a Vertex-polygon-type line

In such kind of patterns implementation, the count of vertexes is not fixed but depends on the length and the curvature of the patterns' lines. Applying the statistical approach used so far is not possible since the number of output parameters is not fixed. However, the authors of this study applied a conversion approach (details to be found in (Neimanis et al., 2025) – refer dxftosvgconverter.zip) allowing to approximate the .dxf polygons with a combination of straights and Bezier curves. The resulting error (e.g., the maximum distance between the lines) is irrelevant to the subject of investigation.

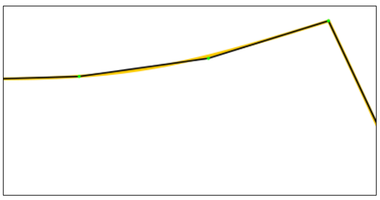

Figure 21. Conversion sample (green/black: vertex-polygon-type, orange: approximation with .svg)

The approach was applied on the output created by an open-source CM/M2M-system (Harwood et al., 2020) which provides the results in that Vertex/polygon-type format. That system is published with several executable pattern samples. We selected similar patterns as discussed above – a base skirt and a sweatshirt. By providing (the partly transferred – refer section 2.2) input data from the test data we created 469 .dxf patterns and applied the above-mentioned conversion to .svg creating the prerequisites to apply the Testing procedure.

Thanks to the Testing procedure, before reviewing any pattern we identified immediately 5 profiles for whom the pattern creation algorithm had created a senseless .dxf result, simply by comparing the number of created lines during the conversion.

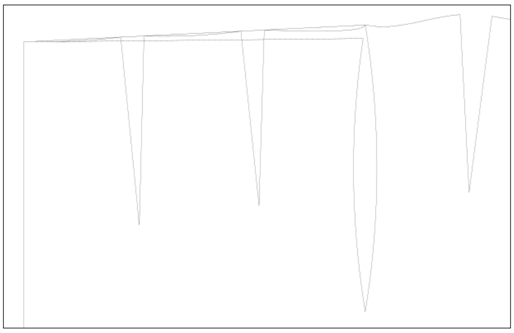

Figure 22. One of five identified senseless results for the skirt in .dxf format

For the remaining 464 profiles results in the same form as described in the previous sections were reached.

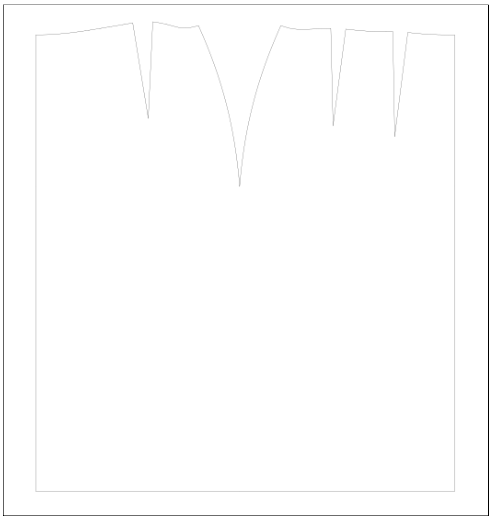

Figure 23. Skirt sample (converted to .svg format)

The analogue execution of the sweatshirt sample, consisting of front, back and two sleeve versions resulted in .svg-files with identical line structure, hence the provided outlier data could be used for detection of potential construction problems.

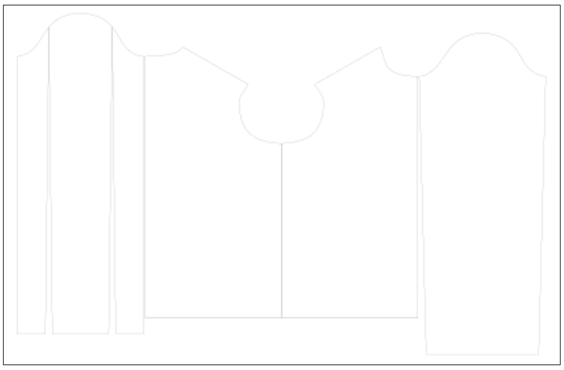

Figure 24. Sweatshirt sample (converted to .svg format)

3. Results

3.1. Piece Level

As discussed in Section 2.4, the correlation coefficients for the piece-level parameters Area and Perimeter differed significantly, even though practical experience suggests that the basic skirt pattern examined here should not exhibit anomalies in its construction.

To investigate the reason for these differences, we closely examined the pattern's algorithm for the waist darts. We found that the number, length, and placement of the darts are not defined continuously but rather in discrete steps. As a result, the prediction of the Perimeter using linear regression is less accurate compared to that of the Area, which is less influenced by the waist darts.

When investigating the reason for the inhomogeneous distribution of Cook's distance (refer Figure 10), we found that a small number of outliers, which are influential data points, also appear to have low credibility. This suggests that the identified outliers are more likely to indicate low-quality body measurements rather than construction errors. Overall, we identified 12 profiles with potentially incorrect measurements, which adversely affect the generated skirt base patterns.

Answer on research question 1: Potential errors in CM/M2M pattern construction can be identified by analyzing quantitatively measurable properties like the area and enclosed surface of pattern pieces' outer contour. Preconditions for a senseful use of the according statistical methods are on the one hand qualitative input data and on the other hand a consistent implementation of the pattern construction for the whole variety of input data. By using the measurements as input for predictive models (e.g., linear regression), and analyzing the deviations between observed and predicted values with Mahalanobis distance, Cook's distance, and residual analysis, the method can detect major outliers and irregularities, highlighting issues such as scaling errors or miscalculations in the pattern construction process.

3.2. Line Level

Similar to the skirt base pattern discussed in the context of potential piece-level failures, the bodice pattern used for line-level failure detection has been well-tested in practice. When investigating the reasons for the numerous outliers in profile 249, discussed at the end of Section 2.5, we found that this profile had already been classified as having "low" credibility in the study presented in Section 2.2. Similar to the piece-level analysis, the line-level analysis is more likely to indicate low-quality input data rather than actual construction errors.

Answer to Research Question 2: Under the same preconditions outlined in the answer to Research Question 1, potential errors in CM/M2M pattern construction can be identified by analyzing the properties of the lines forming the outer contour of pattern pieces. By using body measurements as input for predictive models (e.g., linear regression) and analyzing the deviations between observed and predicted values through residual analysis, this method can detect major outliers and irregularities. It can highlight issues such as scaling errors or miscalculations in the pattern construction process.

4. Conclusions

4.1. Summary

Our investigations indicate that statistically based methods for quality assurance of CM/M2M patterns have great potential for avoiding unnecessary costs in the product development of CM/M2M products. By using the Testing procedure described above, it is possible to determine, even during the development phase, which tested profile's patterns are not fitting into the remaining test data result spectra. Targeted identification of risk candidates accelerates the testing process because, when CM/M2M patterns are programmed, it is important to consider as many possible and realistic measurement combinations as possible. However, due to human factors and time constraints, certain specific cases may remain unprocessed. The goal is to minimize such cases, and outlier analysis serves as a tool to achieve this. By identifying standout profiles, pattern programmers can visually inspect these specific patterns for potential defects without having to review all generated patterns.

The most significant benefit of the Testing procedure, however, lies in uncovering technologically detectable errors before the CM/M2M product is validated through physical tailoring and fittings.

4.2. Usage Hints

The results discussed in Sections 3.1 and 3.2 show that the Testing Procedure loses significant value if the measurement data used as input is of low quality. The general statistical principle "Garbage In, Garbage Out" fully applies to this procedure as well. Therefore, the Testing Procedure requires high-quality body measurement data that adequately covers the entire range of the target buyer group for the tested pattern.

By nature, the Testing Procedure is only applicable if the line structure of the tested pattern's pieces remains identical across all applied body measurement datasets. Furthermore, the poor Perimeter results discussed in Section 3.1 indicate that not every quantitatively measurable property of pattern pieces is inherently suitable for a statistically based testing procedure. To use parameters such as Perimeter, one must either (i) Implement an appropriate segmentation of the test data, or (ii) remove the parameter from the test altogether.

The Testing Procedure delivers meaningful results only for the tested items. The discussion regarding the scye line (see end of Section 2.5 and Section 3.2) suggests that potential issues cannot always be identified by the specific set of tested parameters used in this approach. For highly complex lines that depend on multiple body measurements, it is advisable to split them into equidistant segments before applying the Testing Procedure.

4.3. Practical Application

This publication presents only the results of applying the developed method to base patterns. The authors have begun applying the procedure to much more complex use cases in ongoing CM/M2M product developments. A major challenge will be to avoid being overwhelmed by a flood of data, as the number of lines in a typical CM/M2M product is in the high double digits, and the number of analyzable parameters is in the triple digits. The task is therefore to derive a practical and effective application methodology for the procedure.

Furthermore, in addition to the previously considered .svg and .dxf variants, it is our intention to support additional output formats to expand the range of supported garment construction systems.

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