Visual quality prediction of plastic product based on thermographic images

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Abstract. The main purpose of this study is to control the visual quality in plastic injection moulding using an infrared camera after the ejection of the plastic part. Quality indicators have been extracted from the thermal image and from the data recorded by the sensors in the plastic injection machine and in the mould. After cooling, visual quality has been labelled by plastic experts based on 3 aesthetic defects: spot, flow line and streak mark. Three methods of reducing the dimension of the thermal image were studied: Quantiles, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA). The visual quality can be predicted efficiently using dimension reduction of the image and Partial Least Square (PLS) regression. The PLS results allow to identify the root causes that explain the apparition of visual defects.

Introduction

The injection moulding process is one of the most used processes in the thermoplastic industry. It allows the manufacturing of parts having various shapes with low production time. The quality requirements of injected plastic parts are increasing to guarantee the final product functionality.

For this reason, quality control is widely used in this industry. Methods are often based on statistical grounds [1,[2] and multivariate analysis have been successfully used [3-[5]. In the past, neural networks coupled with fuzzy logic have shown to be efficient in predicting the quality from the parameter settings of the injection machine [6-[11].

However, these works were focused on the modelling of the injection process and have to target a dimensional quality or a weight. The visual quality is more difficult to characterize and to estimate quantitatively [12]. Existing inspection of defects in appearance relies mainly on manual visual inspection, which is neither efficient nor accurate enough to ensure the manufacturing quality. It is all the more difficult to estimate it on a plastic part right after its ejection since its appearance is not yet stabilized due to residual shrinkage.

To analyse the visual quality online, the most straightforward way to proceed is to take a picture of the plastic part right after the ejection, detect any anomaly and evaluate it in order to decide if the product should be accepted or rejected. Artificial Intelligence techniques to extract relevant information about the visual quality can be used. Since the part is still hot right after the ejection, a picture taken with an infrared camera can be a good candidate. Indeed, it has been shown in [13] that the image of the plastic part and its dimensional quality can be efficiently found by taking the hot part of the thermal image.

The most recent advances in this field were summarized in [14]. As noted in this review, studies have been mainly focused on the variation of the injection machine setting parameters. Nagorny [15] presents image analysis techniques based on neural network. It is very powerful to predict the visual quality of the part from the image but the method demands a large number of data to train the model.

In this paper, an alternative technique is introduced to handle the problem, based on dimensional reduction. It is assumed that the relevant information contained in the whole thermal image can be efficiently summarized in a small numbers of components obtained by dimensional reduction.

These components are used as inputs of a machine learning algorithm to predict the visual quality. The good results obtained with this prediction justify our assumption that the thermal image can be summarized in a few components.

This paper is organized as follows: first, the methodology of our work is explained. Secondly, the experimental setup of the work is presented. Next, the different quality criteria used to estimate the visual quality is discussed. Finally, the main results are shown and compared, and the best results are detailed in the last section.

Methods

Our approach is based on the use of dimensional reduction of the image to extract the relevant information in an automatic way.

After different attempts, two dimensional reduction methods were selected: the first one is Principal Component Analysis (PCA), which is well known in data analysis and consists in looking for the axes in the space of variables, which carry the greatest inertia. The second one is Linear Discriminant Analysis (LDA), where best representative axes are looked for taking into account the target quality to be predicted. LDA is also target oriented, since it takes into account the quality we want to predict. For this reason, LDA is expected to be more efficient. This better efficiency will be checked in the results. In this work, both of these methods are implemented using the Scikit-learn package [16] in Python [17].

These two methods provide us with components of the image ranked by decreasing order of importance. Concerning the choice of the number of components to be kept, different ways to proceed exist, but none of them has ever emerged. For this reason, the simplest method, which also seems to be the most reliable, is used [18]. This method consists in plotting the explained variance with respect to the number of components. In the obtained curve, the last inflexion point before the explained variance tends to be constant and vanishing, which gives the number of components, looked for. For instance, we keep components 0, 1, 2 and 3 in Fig. 1 below.

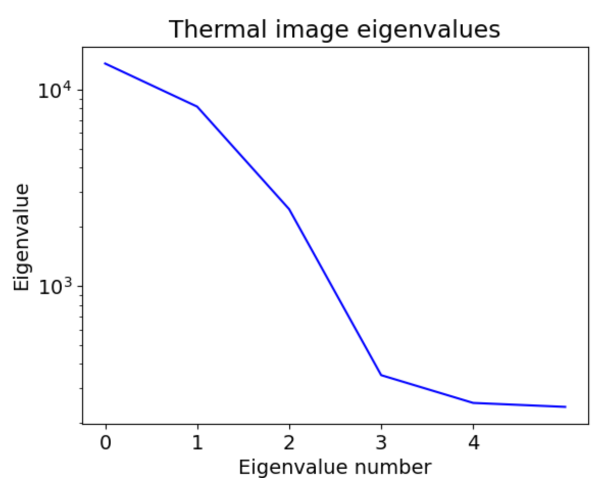

Fig. 1. Illustration of the method to choose the number of thermal image components.

To exhibit the interest of such dimension reduction methods, some quantiles of the thermal image are also computed and used in a way similar to what was done with the dimensional reduction components.

After having selected the correct number of components of the image, the next step is to use them to predict the visual quality. Since this work aims to compare the predictive power of the thermal image indicators and more classical indicators of the process, thermal image indicators and indicators given by sensors in the machine (partially from [19]) are placed in the same dataset. Prediction was then carried out using PLS (Partial Least Square) regression. This regression is similar to an ordinary multilinear regression but is adapted to non-orthogonal input data, which is indeed the case here.

Among the results of this PLS regression, the ranking of all the input variables is shown according to their power to predict the target visual quality. This will also allow us to compare them for this goal, and to show the importance of the thermal image.

Lastly, PLS regression allows making a detailed analysis of the prediction mechanism, which leads to an interpretation of the results in terms of physical root causes. Indeed, PLS regression defines intermediate latent variables, called PLS components, which are orthogonal with each other and which are the basis for an ordinary multilinear regression. These PLS components are computed through a rigorous algorithm, and their number is fixed by prediction tests. The user has no choice to make for these prediction tests that makes the whole process very rigorous. These PLS components can be interpreted as root causes for the output variable we try to predict. PLS regression was performed using the plsRglm package [20-23].

Experimental Setup

A Billion 200T H150/470-200 plastic injection moulding machine was used for the experiments. The plastic material chosen for all the experiments was a black polypropylene "ExonMobil EXXTRAL CMU201" which is often used in the automotive industry. The plastic part was produced by an experimental mould chosen for simplicity to define quality criteria. The plastic part is shown in Fig. 2 below. Its dimensions are approximately 100×100×50 mm.

Fig. 2. Plastic part.

A Staubli robot arm takes the part out of the mould at the ejection and puts it in front of an Optris thermal camera sensitive in a wavelength range from 7.5 to 13 micrometres. For our purpose, it is enough to use the bare thermal camera image. The elapsed time between the mould opening and the image capture was constant and equal to 10 seconds.

The thermal camera picture was reshaped to isolate the plastic part from the background, especially the reflection from the robot arm. This reshaping has been performed using K-Means clustering and DBSCAN algorithm [16] in Python. This is made easy by the fact that the plastic part and the background are clearly separated on the statistical distribution of the pixels. An example of an obtained picture is shown in Fig 3. below. As can be seen on the left, the hot part is limited to the centre near the injection point and the extremity of the plastic part are the parts that have cooled down the quickest. On the right, the cumulative distribution function shows the proportion of pixels below a given temperature: this allows the easy determination of quantiles as the abscissa corresponding to a given ordinate in this curve.

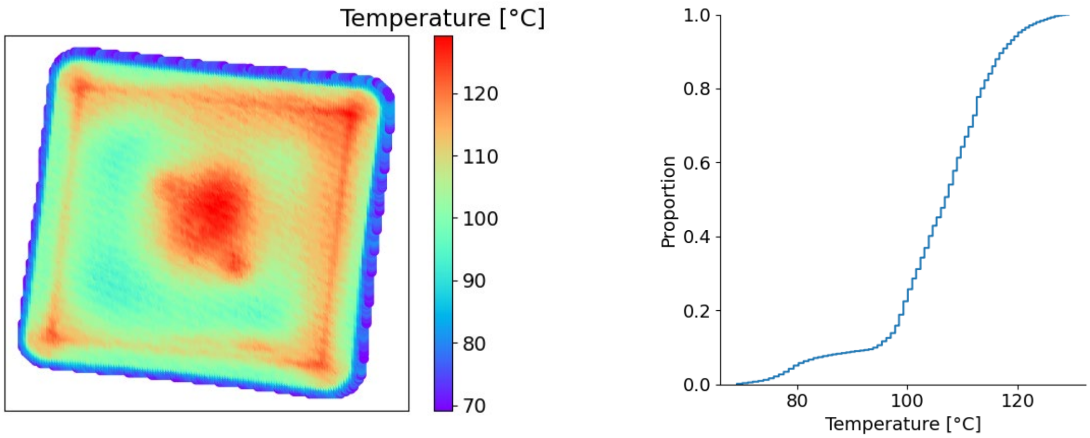

Fig. 3. Reshaped thermal camera picture (left) and empirical cumulative distribution function (right).

The dataset was produced using a L12 Plackett-Burman Design of Experiments [18]. The 11 setting parameters of the injection machine are listed in Table 1 below (together with their minimum and maximum value in this DoE), and have been chosen to ensure repeatability and automatic inline control.

Table 1. Setting parameters for the DoE.

Setting parameters	**Minimum**	**Maximum**
Clamping force	100 t	200 t
Injection stroke	80 cm^3	86 cm^3
Injection speed	50 cm^3/s	90 cm^3/s
Holding pressure	100 bars	300 bars
Controller temperature	20 °C	60 °C
Dosing delay	1 s	10 s
Screw speed	50 tr/min	150 tr/min
Barrel Temperature	220 °C	260 °C
Feeding stroke	90 cm^3	110 cm^3
Opening speed	100 mm/s	120 mm/s
Back Pressure	30 bars	70 bars

Since the thermal picture cannot vary directly, this DoE on the machine parameter setting paramters is the best way to get enough variance on the thermal pictures to be able to build a reliable statistical model to predict the visual quality.

Measurements

Once produced, the plastic parts are cooled down and plastic experts evaluate their quality 2 days later. This delay ensures that the plastic part has fully stabilized. A label is given, ranging from one (perfect) to 10 (the worse), for each of the three following criteria:

1) The presence of spots or sink marks, which come from concave zones in the part and indicate that not enough material has been injected during the holding phase to compensate for the shrinkage. This is because the holding phase was not sufficient.
2) The presence of flow lines (run-out), which come from an excessively large opening time of the mould. While the mould is open, a residual pressure exists in the nozzle that makes

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the plastic material flow into the opened mould. If the opening time is long, a drop of cold material is formed and then crushed by the mould when it closes. In the subsequent process, it forms on the final part a mark around the injection point when surrounded by new material.

3) The presence of streaks around the injection point. When the plastic material is not sufficiently dried before being injected, residual humidity forms water droplets in the part around the injection point, that are visible as white marks in the part.

Finally, a total visual quality is computed as the product of the three qualities defined just above.

Overview of Results

As explained in the previous section, quantiles or dimensional reduction components from the thermal image are extracted, and concatenated to the indicators. A PLS regression is performed in order to predict a visual quality. This is done for Spots quality, Flow lines quality, Streaks quality and Total visual quality. For each quality, a separate PLS regression model is computed. Quality of the prediction is given by R2 (usual measure of quality in regression), which measures the ratio of the variance explained by regression divided by the total variance. Results are given in Table 2 below.

Table 2. Obtained R2 as a function of the considered quality and the input data.

Data Set	Spots quality	Flow lines quality	Streaks quality	Total visual quality
indicators and quantiles of the thermal image	0.780	0.647	0.148	0.349
indicators and principal components of the thermal image	0.839	0.764	0.349	0.343
indicators and LDA components of the thermal image	0.919	0.950	0.830	0.400

As can be seen from Table 2, a much more powerful way to predict the visual quality is to use the dimensional reduction instead of using only quantiles from the thermal image. In fact, R2 is better for each quality in the last two lines of Table 2 rather than in the first one, which concerns quantiles. For each quality, Table 2 shows that the best R2 result is obtained for LDA reduction. This is expected, since LDA reduction computes the components taking into account the target quality, which is not the case with the other dimension reduction methods.

In the last column of Table 2, it is noticed that the prediction performance of the total visual quality remains poor (R2=0.4) whatever the dimensional reduction of the thermal image is. This is because the total visual quality is the product of the three basic qualities (spots, flow lines and streaks). This product has great uncertainty compared to the uncertainties of the basic qualities since some values of the basic qualities can be important. This makes the total visual quality more difficult to predict.

Detailed Results

As seen in Table 2 above, LDA dimensional reduction provides the best regression. In this section, these results are analysed using the interpretation allowed by PLS regression.

Spots quality.

With the criterion of the inflexion point in the explained variance (see section “Methods”), six LDA components are kept. Main standardized coefficients (i.e. those greater than 0.1 in absolute value) of the PLS regression for spots quality prediction are given in Table 3 below.

Table 3. Main standardized coefficients for spots quality prediction.

Variable	Standardized Coefficient
First LDA component	0.259
Viscosity during the holding phase	0.241
Third LDA component	0.202
Mould viscosity during the holding phase	0.180
(…)	(…)
Second LDA component	-0.275

This table shows that the thermal image summarized by LDA component is highly relevant to explain spots quality: the interpretation of each LDA component is not available, but it can be noticed that the highest positive coefficient is held by the first LDA component and the smallest negative coefficient is held by the second LDA component. Since they are the most important LDA components, they are connected to the global homogeneity of the image and spots are connected with visual defects that have an importance on the global scale. This is expected from a visual inspection of the plastic parts.

Moreover, spots are due to a lack of material caused by an insufficient holding. In Table 3, it is found that a high viscosity in the holding phase, in the machine and in the mould, increases the spots quality. The viscosity is computed as the pressure integral in the holding phase. So Table 3 says that having a high pressure during holding increases the spots quality, that is what is expected from the definition of spots (sink marks) in section "Measurements".

In the next table, such an interpretation is examined to identify the root causes of the spots quality in a more detailed way than with the standardized coefficients (Table 3). For the spots quality, the algorithm tells us to keep 4 PLS components.

The root causes to improve the spots quality provided by PLS components are summarized in Table 4 below. To keep the paper brief, we shall skip the detailed analysis and the justification of these results.

Table 4. Summary of PLS component interpretation for spots quality.

PLS component	Interpretation
1	Increase the pressure integral during the holding phase
2	Same as 1, plus increase the volume of polymer available for injection; also look at the thermal image in detail
3	Analyse the thermal image
4	Same as 3

Flow lines quality.

With the criterion of the inflexion point in the explained variance (see section "Methods"), 6 LDA components are kept. Main standardized coefficients (i.e. those greater than 0.1 in absolute value) are shown in Table 5 below.

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Table 5. Main standardized coefficients for the flow lines quality prediction.

Variable	Coefficient
First LDA component	0.659
Fifth LDA component	0.149
Injected volume during the dynamic phase	0.106
(…)	(…)
Third LDA component	-0.109
Fourth LDA component	-0.121
Viscosity during the holding phase	-0.159
Viscosity during the dynamic phase	-0.196
Second LDA component	-0.307

The Table 5 shows that the standardized coefficients are clearly dominated by the thermal image and, in particular, the first and second LDA components. This shows that flow lines are visible on a global scale on the thermal image, and so that the thermal image is very relevant to explain the presence of flow lines (the LDA components have been calculated with respect to the flow lines quality, and have also changed compared to the spots quality case). Compared with the spots quality, it is noticed that the viscosity in the holding and dynamical phase acts negatively this time. Indeed, to have a good flow lines quality, the residual pressure after mould opening must be low, that is easier if the pressure imposed during the injection and the holding has been low (see section “Measurements” for physical causes).

Statistical tests on prediction power indicate to keep 4 PLS components. The root causes obtained for the interpretation of the four PLS component are summarized in Table 6 below.

Table 6. Summary of PLS component interpretation for flow lines quality.

PLS component	Interpretation
1	Inject the polymer early and not during the holding phase right before the mould opening, which may cause some flow of the polymer in the opened mould
2	Cool down the plastic part efficiently to avoid flow lines, which means that an efficient cooling must solidify the sprue
3	Inject a large quantity of polymer for the residual quantity of polymer in the machine to become low, and to have a low residual pressure
4	Inject all the available polymer volume, so there remains nothing to flow in the mould during mould opening

Streaks quality.

With the criterion of the inflexion point in the explained variance (see section “Methods”), we keep 4 LDA components. Main standardized coefficients (i.e. those greater than 0.05 in absolute value) are shown in Table 7 below.

Table 7. Main standardized coefficients for the streaks quality prediction.

Variable	**Coefficient**
First LDA component	0.831
Viscosity during the dynamic phase	0.095
Thermal controller mean flow rate	0.076
Fourth LDA component	0.072
(…)	(…)
Third LDA component	-0.055
End of feeding time	-0.069

What is visible in this Table 7 is that almost everything is explained by the first LDA component. For consistency with other analysed qualities, we look also at the PLS components. Statistical tests on prediction power tell to keep 4 PLS components.

The interpretation of the four PLS component as root causes are summarized in Table 8 below.

Table 8. Summary of the PLS component interpretation for streaks quality.

PLS component	**Interpretation**
1	Lower the polymer temperature at all stages to avoid the formation of water vapour bubbles
2	Increase the pressure during the holding phase to avoid droplets to form.
3	Augment the pressure drop in the nozzle to avoid shear in the mould (which causes heating and formation of water vapour bubbles)
4	Decrease pressure and injected volume during the holding phase, which decreases the shear in the mould and so the polymer heating.

Total visual quality.

The PLS regression leads to a R2 equal to 0.4, which is too small for the interpretation of the coefficients to be possible.

Summary

In this paper, the visual quality prediction of injected plastic boxes based on dimensional reduction is studied. Three methods of reducing the dimension of the thermal image are studied: quantiles, Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA). The prediction of the quality marks is achieved from a dataset gathering dimensional reduction and from indicators calculated from the machine and mould sensors. The best results are obtained with the LDA dimensional reduction whose interpretation enable to define root causes explaining the phenomena.

The presented work shows that the dimensional reduction method is validated and is a much simpler alternative for visual quality prediction than neural networks, which demand a huge amount of data. The statistical analysis interpretation shows also that it is possible to refine human experts' evaluation and knowledge, to evaluate their notation and can help ~~to~~ define a human evaluation procedure.

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