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A new approach to the evaluation of forming limits in sheet metal forming

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Abstract. The forming limit diagram (FLD) is at the moment the most important method for the prediction of failure within sheet metal forming operations. Key idea is the detection of the onset of necking in dependency of different strain behaviours. Whereas the standardized evaluation methods provide very robust and reliable results for conventional materials like deep drawing steels, the determined forming limits for modern light materials are often too conservative due to the different failure behaviour. Therefore, within this contribution a new and innovative approach for the evaluation and analysis of material behaviour will be presented. Thereby the complete strain history during the test is evaluated using a pattern recognition-based approach in combination with an optical strain measurement system. The basic procedure as well as the first promising results are presented and discussed.

Introduction and state of the art

The FLD is used in sheet metal forming for the evaluation of the forming limit. Its concept was introduced by Keeler in 1963 [1] and it shows the major and minor strain values of failure for different strain modes. By testing different stretch conditions, the major and minor strain are sampled at the onset of necking and build the forming limit curve (FLC). The FLC distinguishes between safe and necked state and can be used to predict the forming behaviour in complex sheet metal forming processes. An example of the FLC is depicted in Fig. 1. By varying the width of the specimen it is possible to collect strain conditions from a biaxial mode to simple tension state (see also Fig.2). The represented strain paths are representative for a sample with a width of 125 mm and 60 mm. The procedure to determine the FLC is standardized by the ISO 12004-2 [2], which prescribes two possible test setups: the Marciniak [3] and the Nakajima test [4]. Both provide the use of a blank holder system and a punch, which is flat in the Marciniak test setup and hemispherical for the Nakajima test. In both cases the sample is deformed until failure and the strain values are measured in the zone where the crack occurs. The first arrangement to collect information about the strain condition was a grid of circles on the workpiece and the results were determined by measuring the deformation of the circles. In the last 20 years the procedure has been improved by introducing optical strain measurement based on digital image correlation technique (DIC) [5]. The sample surface is sprayed with white varnish and graphite in order to achieve a speckle pattern distribution. Modern optical measurement systems provide very accurate strain measurement covering the entire forming experiment. However, the standardized evaluation method position-dependent und does not use the strain path development during the test. In recent years, new time-dependent evaluation procedures have been proposed in order to improve the standard method. The line fit method [6] suggested by Volk analyses the thickness reduction in the critical zone and detects the onset of necking as a sudden change in the thickness reduction path.

The correlation coefficient method [7] is based on the major strain path in order to determine the onset of necking as the maximum value of the coefficient of correlation of the strain acceleration development. These methods show very good agreement with the experimental results and represent a good alternative to the standard method. However, the basic idea of the methods is still depending on the strain development estimated in a small area around the crack initiation. As a consequence the evaluation does not consider the development of the material structure and the onset of necking can only be detected indirectly. Within this study a direct investigation of the sheet metal is performed by applying a pattern recognition analysis.

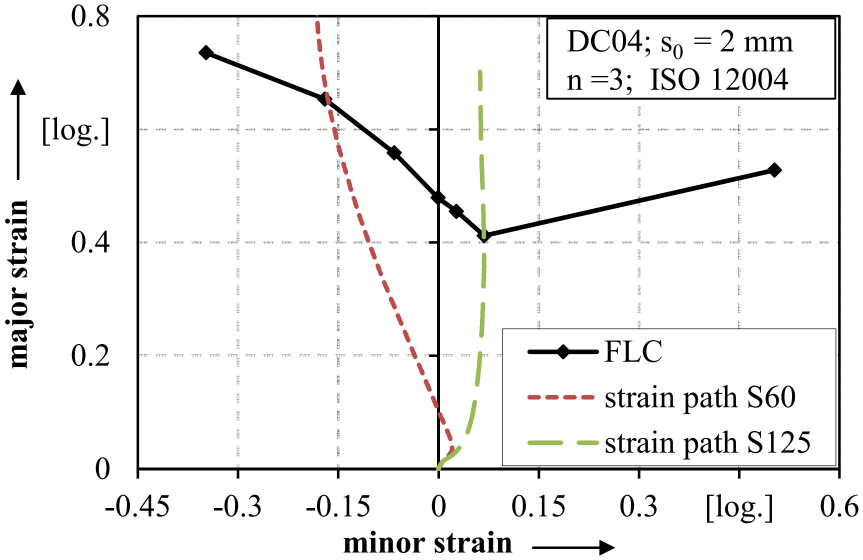

Figure 1: Forming limit curve according to ISO 1004-2 for a DC04 with a thickness of 2 mm and strain path development for a sample 125 mm and 60 mm width (see also Fig. 2).

Generally, pattern recognition deals with the problem of assigning a class or a prediction value to a given signal. The former concerns a classification problem while the latter is usually analysed with a regression analysis. In both cases, the pattern recognition has been successfully applied in many signal processing applications [8]. Pattern recognition is also referred to as machine learning in literature [9] It was applied to several problems ranging from speech processing [10] to (medical) image analysis [11]. Nevertheless, up to now there are nearly no applications in sheet metal forming processes. Within this paper, pattern recognition is applied to the optical measurement data collected from several Nakajima tests.

Experimental setup and procedure

Nakajima test setup. For the present investigation a Nakajima testing machine was used. In order to determine a discrete number of points for the FLC eight geometries have been examined with three repetitions. Figure 2 schematically shows the test setup as well as the used sample geometries. The sample is clamped between the blank holder and the die and the punch progresses in vertical direction in order to form the sample until fracture. The setup is equipped with the optical strain measurement system Aramis (GOM) for sampling 3D-pictures of the test.
Material. For the present study, a DC04 is selected as specimen material with a sheet thickness of 2 mm. DC04 is a mild steel for cold forming applications with a discrete formability and relatively high strength. It is usually used in the automotive industry for internal as well as external parts. Due its good forming behaviour is often used as reference material.

Process parameter. After cleaning the specimen with acetone a lubrication system with grease, Teflon foil and Mipolam is used in order to reduce the friction between the punch and the specimen. The clamping force applied from the blank holder is 720 kN in order to avoid any material flow from the flange. The tests are performed with a constant punch velocity of 2 mm/s and the pictures are taken with a sampling rate of 20 Hz.

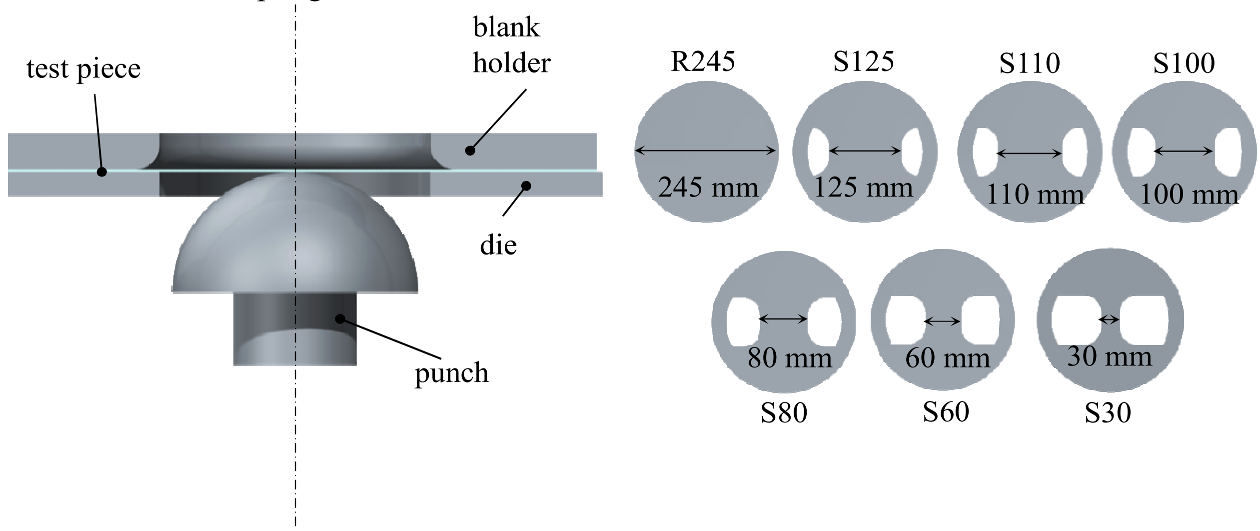

Figure 2: Nakajima test setup and sample geometries for the determination of the forming limit curve.

Pattern recognition

The data analysis procedure of the acquired images can be expressed in a diagram as illustrated in Fig. 3. The images are recorded by camera sensors leading to a digital representation of the underlying problem. To improve the results and facilitate the classification task, the images are *preprocessed*. This step includes procedures to reduce signal impairments like noise and other artefacts as well as methods to normalize the signal. In the present study, the *preprocessing* step extracts the three principal strains ε_1 (x,y,t) , ε_2 (x,y,t), ε_3 (x,y,t) for each point with (x,y) coordinates at time t from the begin to the end of the test. During the *feature extraction* step, a characteristic vector *x* for every time step is extracted describing the image and its properties by computing different numerical indicators. The vector x is defined as described by Eq. 1 and Eq. 2.

$$\mathbf{x} = (\boldsymbol{\varepsilon}\,(x,y,t)^T\ \boldsymbol{\varepsilon}\,(x,y,t-1)^T \ldots.\ \boldsymbol{\varepsilon}\,(x,y,t-t_n)^T)^T \quad (1)$$

$$\boldsymbol{\varepsilon}\,(x,y,t)^T = (\varepsilon_1\,(x,y,t)\ ,\ \varepsilon_2\,(x,y,t),\ \varepsilon_3\,(x,y,t)\ ). \quad (2)$$

The resulting feature vector contains the deformation in the three principal directions at the current time t plus (t_n -1) prior observations. For the remainder of this paper the value t_n is set to 20 for initial experiments. Therefore, the pattern recognition analysis will use the information of the last 20 frames, which corresponds to one second.

The *feature selection* procedure is optional and omitted in the present study. In fact, in spite of best correlation with the images, the application of a feature selection procedure can reduce redundant information introduced by other features of the characteristic vector in the case of forming processes and that would affect the classification results negatively. The subsequent *classification* task uses the characteristic vector to separate the different classes, for instance by using the so called "random forests" classifier [12]. A random forest classifier is built from many random tree classifiers. The random tree is a special case of a decision tree classifier that selects a random subset of feature vectors and a random number of features for the training of each classifier.

In practice more than 100 such trees are built and the class is selected by majority decision. The random subset projection makes the training efficient and robust to outliers. First, the data set is split into a training set and a test set. The classifier uses the training set to find an optimal separation of the different classes. The test set is then subjected to the trained classifier to validate the separation hypothesis and to compute quality characteristics like the sensitivity or specificity to evaluate the classifier. In this study, a random data subset has been chosen to build random forest classifiers. The classification task is set to "*current pixel will be broken in next image*" vs. "*current pixel will not be broken*". The regression task is to predict how many steps the sample at the current position can take before a crack occurs. In order to generalize the results, data of different specimen is used for training and tests.

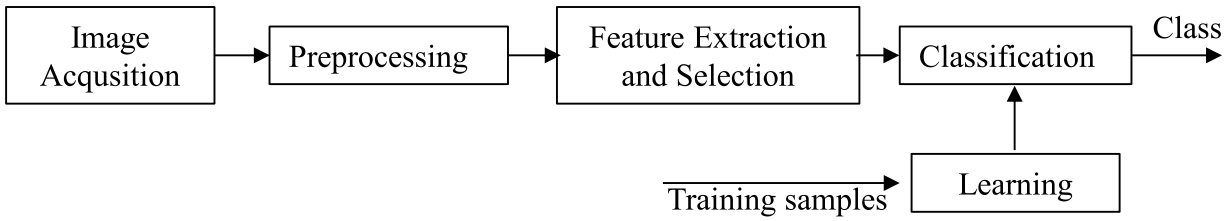

Figure 3: Scheme of the pattern recognition pipeline.

In the present study, a preliminary regression analysis is carried out in addition to the classification approach with the goal to make a comparison of the results. In order to generate training data for the regression and classification system, each recorded image sequence is examined to determine the first point in time when the crack occurs at every pixel. From this information, it is possible to identify feature vectors that would break in the next frame for the classification experiment. Counter examples (defined as vectors related to pixels that are not going to crack at the next time step) are randomly generated from the dataset to form the data for the classification experiment. Furthermore, feature vectors are extracted from pixels that will break within the sequence to obtain data for the regression experiment. For each feature vector, the difference from its current time to the point in time when the pixel will break is recorded. In this manner, each feature vector the remaining time until it will break is assigned to build data for the regression experiment.

Results

The training analysis is conducted first on one sample per width (Fig. 2) and finally on all available training data across all geometries. The results from the classification and regression analysis are listed in Table 1. The outcomes show good agreement with the experimental results for the classification approach for each strain condition represented by the different test width. The classification task using only training data from the same sample type classified an average of 91.26% of the cases correctly. That means that it is possible to identify the crack zone one frame before it occurs with an accuracy of about 91.26%. The regression outcomes are expressed in terms of correlation coefficients and depict values greater than 0.99 with an absolute error below 5 frames. With the use of all available training data across all sample types a further slight improvement to 92.04% for classification and a slight increase from 0.9993 to 0.9994 for the correlation coefficient is achieved. The average mean absolute error, however, is slightly increased from 4.30 to 4.34 frames.

It is not possible to identify a trend in the classification result in terms of strain distribution. However, the accuracy of the pattern recognition depicts the best result in the case of negative minor strain values (left side on the FLC), with an average of an absolute error of 2-3 frames instead of 7-8 frames for the R245 and S125 geometry. This result can also be explained by examining the section length of the test (in terms of frames). In the case of the R245 the specimen is under biaxial strain condition. It is formed with a relatively long, stable and uniform strain distribution. The crack occurs before a localized necking can be observed. Therefore there are less training data that present instable behaviour and thus the classification by using one training data set delivered worse results. Interestingly, using all samples for the training improves the classification results not only for the biaxial condition but also for the other geometries. It can be affirmed that even if the tests happen under different strain conditions, the outcomes collected for one case give additional information that can be applied to predict different strain conditions. An exception is represented by the sample with 110 mm width. In this case only few training samples were collected as the crack covered only a small area on the workpiece. Thus it was difficult to generate a sufficient amount of training and test samples. In consequence the results should be interpreted with care in this case.

Generally, the results depicted from the regression methods are very promising independently of geometry and training strategy. In terms of absolute error, there is no consistent trend between the different geometries. The absolute error in frames is sometimes slightly higher using the complete training data.

Table 1: Results from the pattern recognition analysis for each tested geometry by the Nakajima setup.

Data		One sample training data			All training data		
Sample geometry	Sequence length [frames]	Regression (coeff. of correlation) [-]	Classific. [%]	Mean abs error [frames]	Regression (coeff. of correlation) [-]	Classific. [%]	Mean abs error [frames]
S30	213	0.9992	91.16	1.88	0.9992	93.18	2.14
S60	245	0.9979	93.75	3.6	0.9986	94.04	2.99
S80	275	0.9998	95.68	2.13	0.9997	96.12	2.57
S100	325	0.9997	90.18	3.34	0.9995	90.74	2.89
S110	336	0.9998	90.00	3.47	0.9998	87.74	3.97
S125	373	0.9990	88.42	7.91	0.9990	89.53	7.99
R245	520	0.9997	89.62	7.80	0.9997	92.96	7.81
Avg.	**327**	**0.9993**	**91.26**	**4.30**	**0.9994**	**92.04**	**4.34**

Conclusion and outlook

In the present study, an innovative approach by using pattern recognition is used in order to predict the crack initiation during Nakajima tests for DC04 steel. The strain history during the test is recorded with the optical measurement system Aramis in term of principal strains. The regression as well as the classification approach has been investigated towards the detection of crack initiation using a history of 20 frames. Both methods have shown promising results. The classification outcome rates of about 90% for each strain condition by using one sample but the application of training using all data provides more accurate results. The regression system is also accurate with an average of 0.999 for the coefficient of correlation. The strain condition does not have a direct effect on the accuracy of the method. But it can influence the sequence length of the data. That would affect the training process with a higher sequence length, e.g. for biaxial strain conditions. Further investigation will focus on the influence of limiting the training to a specified period in time. In addition, the promising results for DC04 must be validated for other materials. In particular the transfer of the approach to modern sheet metals like aluminium alloys or high strength steel will be interesting. The complexity presented by these materials is directly related to the different strain development under different stress condition as well as the relatively scarce information available about their instable behaviour from onset of necking to crack. It is expected that the prediction of the initiation of necking will be harder than the prediction of cracking for these materials. In this case the challenge is to correctly define the classification task, which strongly depends on the definition of necking in terms of changes on the material surface. The auspicious approach is to conduct a metallographic investigation in parallel to the pattern recognition in order to achieve a detailed description of the problem by its physical aspects.

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