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An online intelligent algorithm pipeline for the elimination of springback effect during sheet metal bending

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Abstract

An intelligent control algorithm pipeline is proposed to eliminate the effects of variation of physical properties of sheet metals on bending. This pipeline can be applied to any conventional press brake without the necessity of additional sensors and/or equipment. The overall pipeline is capable of extracting features representing sheet metal during bending in an online manner, classifying it accordingly, running a neural network model specific to the classified material, and calculating the correct punch displacement in order to eliminate springback effect. Moreover, algorithm pipeline can also decide whether the material processed is already in the material database or not. If the material is not in the material database, it directs the user in order to generate a quick reference model for completing the bending procedure and adds this model in the material database. The overall algorithm pipeline provides an autonomous approach to material bending and saves time by eliminating tedious calibration and bending iterations.

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Keywords: Sheet Bending; Material Identification; Machine Learning; Neural Networks; Classification; Anomaly Detection

1. Introduction

Sheet metal forming is a highly developed and effective technique for mass production. However, the process itself has some fallbacks such as the vulnerability to the variation of physical properties of materials processed and these would increase the production time. A press brake is composed of a mechanical structure, a hydraulic drive system

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and an electronic control unit. The sheet metal bent on press brake actually completes the overall mechanical model of the press brake and affects the performance and functioning of the press brake in every manner. Accurate evaluation of material behavior is the crucial aspect to study for attaining suitable metal-forming analyses, simulations and results [1]. Moreover, the behavior of the material affects the quality and the pace of the production drastically. During the production process, some iterations or calibrations would be required for different types of sheet metals (even the different batches of the same material) in order to get the accurate bending output. In other words, physical properties of the same material from different batches would vary significantly, and for each and every different batch of material, a production calibration is generally required.

Nomenclature

V	width of V-opening of the die
$R_{p/d}$	radius of the punch tip / die sides
t	thickness of sheet metal
β	angle that supplements the bending angle
z	needed punch penetration to bend the sheet metal to (180-ß) degrees

The desired target of a bending operation is the final bent angle of the sheet metal processed by the press brake and the input to the system is the desired angle. It is taken by the press brake system and a displacement command is generated by the control unit and this command is followed by the hydraulic drive system to deform and bend the sheet metal bent to the desired angle. However, in this system there is no feedback of the output to the system (Fig.1.(a)).

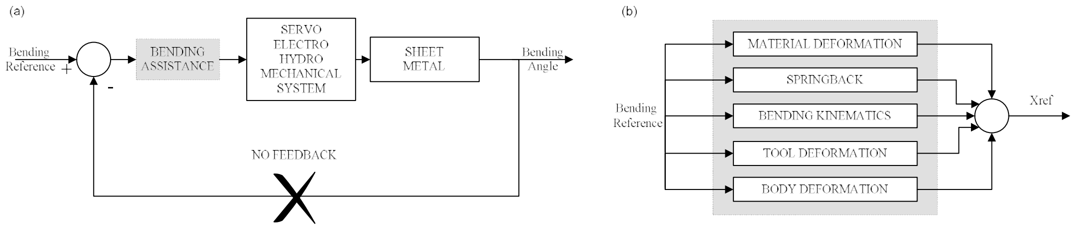

Fig. 1. (a) Sheet metal bending overview; (b) Sheet metal bending assistance module.

The variations or uncertainties on physical properties of the materials as well as mechanical system should be predicted beforehand to improve the quality and accuracy of bending. Therefore, a feedforward mechanism or module (see Fig.1.(b)) should be added to the system. These variations or uncertainties could be on material properties, such as elastic and plastic behaviors of the materials as well as the tooling and the body of the machine. The input parameters for bending has to be based on values provided by the steel manufacturers, values from standards or material certificates, or from on-site material tests. However, these values are never exact, but reflect some ranges which parameters can vary. Moreover, the changes in environmental conditions would also affect the performance of the press brake. A thorough survey on physical properties and environmental conditions affecting bending was presented in a previous study [2]. To compensate the uncertainties and variations for accurate bending, quality analytical or black box models should be generated for each uncertainty in bending or for their overall effect. Then the bending reference command should be regulated according to these models before feeding to the press brake system. The proposed bending assistance module improve the quality of bending utilizing information collected during bending on a machine learning structure for eliminating these uncertainties and variations.

$$z = \frac{V}{2}\tan\left(\frac{\beta}{2}\right) + \left[1 - \sec\left(\frac{\beta}{2}\right)\right]\left(R_p + R_d + t\right) \quad (1)$$

Bending kinematics of air bending (three-point bending/V-bending) are discussed with the assumption of no slippage of the sheet on the press brake V-die in several studies [3]. Bending kinematics is a geometric calculation that provides information for the preliminary value of punch displacement regarding the material and punch are rigid. The geometrical calculation of punch displacement for having the desired bending angle can be expressed in a single formulation (Eq.1), utilizing die and punch radii, bending angle and sheet metal thickness as inputs and returns the necessary punch displacement without taking material type of the sheet metal into consideration (Fig.2.(b)). This formulation is a starting point for searching the correct and accurate punch penetration [3].

Several studies have been carried out for compensating the adverse effects on bending operation by using neural networks (NNs). Forcellese *et al* constructed a NN for springback control but model was constructed only for a specific type of material [4]. In another study, Cao made use of NN with using a stepped binder force trajectory [5]. Inamdar *et al* utilized a NN applied the model to 5 different materials with the same thicknesses and collected 400 points of data before training the model [6]. Casalino and Ludovico applied NN structure to laser bending for one material using a bulky procedure to find an optimum size for the network [7]. Pathak *et al* used results of finite element analyses (FEAs) as input to NN and gets several relevant outputs for springback compensation [8]. Liu *et al* proposed a method combining genetic algorithm (GA) with NN for springback prediction. However, the method required great deal of offline data for precision [9]. Fu *et al* combined three methods, namely; FEA, NN and GA for optimizing the multiple step incremental air-bending of sheet metals [10]. Most of the studies either lack applicability on various material types or depend on extensive experimental data collection before the bending. This study aims removing these two dependencies with the proposed intelligent algorithm pipeline.

2. Proposed intelligent algorithm pipeline

Several intelligent algorithms in literature either needs prior knowledge on materials or can only be applied for a single type of material. In order to remove these dependencies, an intelligent algorithm pipeline is constructed (Fig.2.(a)). Proposed algorithm pipeline is applicable to any conventional press brake, which can supply cylinder pressures, and no additional sensor is necessary for realization. Proposed pipeline can be installed in the control unit of press brake system with the algorithms are running in a CPU installed. The press brake control unit should be altered in order to follow the scenarios given in Fig.5.(a).

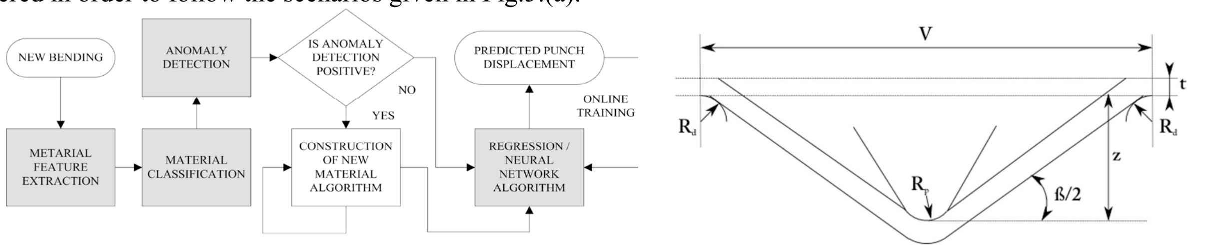

Fig. 2. (a) Proposed intelligent algorithm pipeline for sheet metal bending; (b) Air bending schematic

The pipeline consists of four main parts. These are material feature extraction, material classification, anomaly detection and estimation using Neural Network (NN) algorithm generated for a specific material. During the bending operation, several physical properties of sheet metal (force reactions at specific locations, material thickness, etc.) and operational states and properties of press brake (die width, die radius, punch velocity, etc.) are used in order to construct a feature matrix for the representation of the sheet metal bent. Feature matrix may purely consist of the property values as well as several variations or combinations of them. Then using the classification algorithm, system classifies the type of material according to the new set of features using the material feature database constructed beforehand. Recently bent material is labeled as one of the materials in the database. However, it is necessary to check whether the classification of the material is correct. A brand-new material may be labeled as a database material due to its similar features. For that reason, anomaly detection algorithm is executed. If the material turns out to be a “brand-new” one after anomaly detection, user is directed to collect more data on that material for construction of its own NN structure. If recently bent material is not a “brand-new” one and labeled correctly as one of the database materials, desired punch displacement is calculated using the material specific NN structure. Moreover, by measuring the final bent angle with a proposed method requiring no additional sensor, that NN structure would be updated, in other words is trained in an online manner.

The final bending angle can be measured by using the “available” two sensors installed in the press brake. These are punch displacement sensor and pressure transducers in the press cylinders. After the material bent, punch retracted up and due to springback effect material moves up. Then the punch is moved downwards slowly ensuring 100 nanometers positioning accuracy until it touches the material. Using the punch displacement value at the instance of touch, final bending angle can be retrieved using the geometric bending relation (Eq.1). The moment of touch is decided by the instant jump in pressure values. To verify the validity of this calculation, punch displacement values at the instant of material touch is retrieved for 100 different data points and the retrieved angle values are compared to the real angle values measured using an angle meter with a resolution of 0.01 degrees (Fig.4.(c)).

2.1. Material feature extraction

The features used in the algorithms basically composed of two parts, input and output vectors. Input vector composed of two type of features, ones that represent material properties and the ones that represent bending environment or press brake configuration (PBC). Output vector consists of correct punch displacement value. In Table 1, input parameters are listed. Seven of them are representing material properties, three of them are representing bending environment properties and two of them are representing both. Using these parameters, normalized features are constructed representing the bending phenomenon of a specific material. The physical properties of the material are not identified directly but features representing physical properties are extracted and fed into neural network system so mimicking behavior of the material is achieved.

In order to gather information on material, force reactions on material is retrieved at four points during pressing phase. They are obtained by using pressure values in the press brake cylinders. Data collected in a single bending cycle is represented in Fig.3.(a). The material touch point is taken as '0' for punch displacement. Bending starts when the punch touches the material and ends when it loses contact. The total displacement of punch, which is also the bending reference given to the control unit and known, while in contact with the material is divided equally into four regions and bending regions are constructed as depicted in Fig.3.(b). Force values at the end of this regions (X_1-X_3) and slopes within in each region (X_4-X_7) are taken as features mimicking physical properties of material during bending. Other features given in Table 1 are feature which are known at the beginning of every bending.

Table 1. Normalized Input Parameters

Input Feature	Symbol	Type	Input Feature	Symbol	Type
Force in Bending Region-1 (BR1)/BR2/BR3	X_1, X_2, X_3	Material	Die Property	X_{10}	Both
Average Local Stiffness in BR1/BR2/BR3/BR4	X_4, X_5, X_6, X_7	Material	Punch Radius	X_{11}	PBC
Material Thickness	X_8	Material	Velocity of Punch	X_{12}	PBC
Desired Bending Angle	X_9	Both			

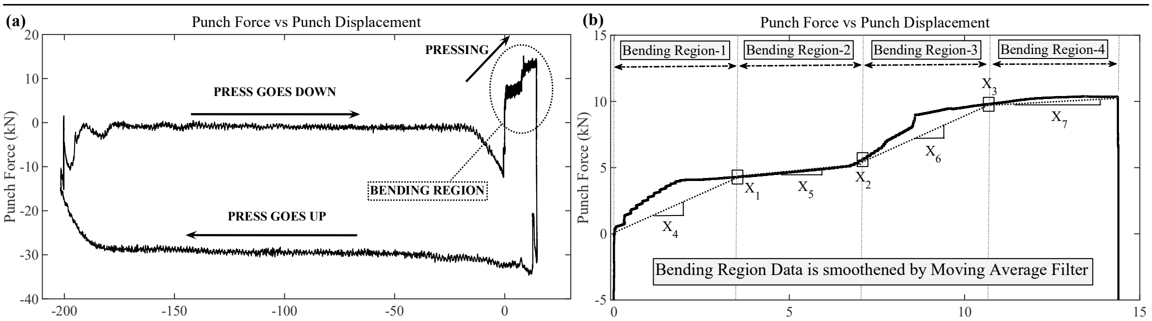

Fig. 3.(a) Single bending cycle of a press brake; (b) Features extracted from bending region

2.2. Classification of different types of materials

After the features of material bent are extracted, material is ready to be classified. Classification algorithm used is K-means clustering but SVM or Logistic Regression algorithms can also be used. When the database is constructed, all of the material-based features in the database are fed to the clustering algorithm. The algorithm make use of the unlabeled material based features and the number of materials in the database. Then using K-means Clustering Algorithm, it computes the centroid of the features for every material in the database as a classifier. A sample run of K-means Clustering Algorithm for three different materials in the database is performed. Since the feature space for materials is 8-dimensional, Principal Component Analysis method is used to reduce feature space to 2-dimensions. In Fig.4.(a), the clustering of three different material types are depicted, and the centroids of each material are shown.

2.3. Anomaly detection of sheet metals with unfamiliar material

At every bending event, material features are extracted and according to the extracted features sheet metal bent is classified as one of the materials in the database. However, the sheet metal bent may be totally a different material. In order to make that sure, a test called anomaly detection is executed. Anomaly detection is a method to decide the outliers in a dataset. Using the data points of a dataset, a Gaussian or another suitable probability model is fitted and this probability model is trained with the available dataset to decide a threshold value for specifying outliers. As an example, a Gaussian distribution is fitted using the data points of ST37-2 dataset. The probability model is trained using available data points to find an outlier threshold. The contour plot of probability distribution model of ST37-2 is depicted in Fig.4.(b). Outlier threshold value is calculated as the inner circle. Therefore, any new data point with a model outcome smaller than 0.01 is decided as an outlier and marked with a diamond. In other words, these data points are accepted as a totally different material. For every different material in the database, a probability model has been constructed. The threshold value for detection of outliers is computed.

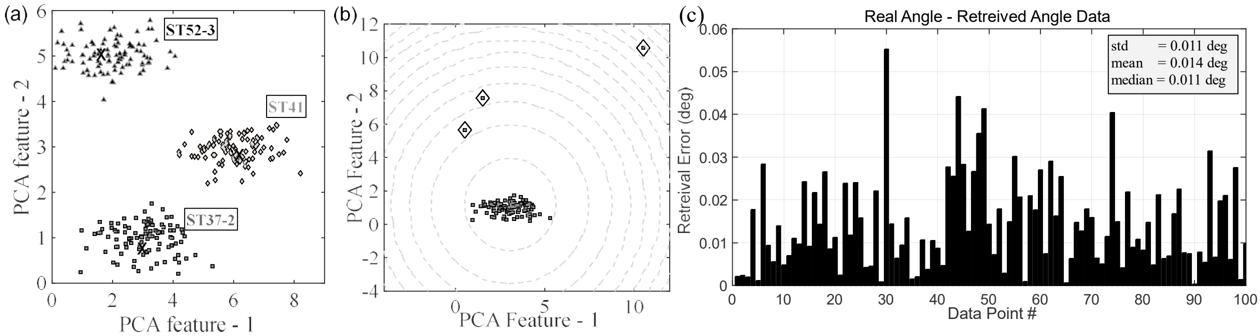

Fig. 4 (a) Clustering of three different material types; (b) Anomaly detection for ST37-2; (c) Difference between real vs measured angle values

2.4. Constructed neural network structure for springback prediction

A standard NN structure (see Fig.5.(b)) with one input layer, one hidden layer and one output layer is used for the last part of the intelligent algorithm pipeline. 3 different input layer structures and 3 different hidden layer configurations, summing up into 9 different NN configurations (Table 2), are constructed and tested. The constructed NN structure differs from its counterparts in literature in the manner of updating function. Since the constructed NN updates the weights after every new bending event, it does not need a bulk training data at once. This update feature validates the applicability of the algorithm pipeline on a press brake in an online manner and without intervention.

3. Results and Conclusion

In order to validate the proposed algorithm pipeline, 100 different bending operations are completed for 3 different materials (ST37-2, ST41, ST52-3) with 3 different thicknesses (1-1.5-3 mm) in 4 different die configurations (V=16-22-35-50 mm). For each material, 3×4×100=1200 data points are available for training, cross validation and testing. 700 of these are used for training the data, 250 of these are used for the cross validation and finally 250 data points are used for testing. For training purposes, 700 bending events are selected for each of three materials randomly. Total 2100 bending events are carried out in random order and mixed for different material types. After every bending event, system extracted features in an online manner, classified the material, and trained the relevant NN. Prediction error is calculated as the difference with the correct and the predicted punch displacement values. Algorithm can be regarded as successful for error values below the position control accuracy (mostly around 1000 nanometers) of the press brake used. Cumulative training times, Mean Absolute Error (MAE) and Maximum Error (ME) results for 9 different NN configurations for each material are given in Table 2. As the outcomes are examined, it can be seen that algorithm utilizing only linear features was insufficient in performance (Average error > 1000 nm). Algorithms with 2nd order polynomial features have better performance and algorithms with 3rd order polynomials have the best performance. However, using higher order features brings a computational cost on algorithms, the necessity of higher order polynomial should be examined. Moreover, there is a trend for neural networks such that as the number of hidden neurons (HNs) in the hidden layer increase the mean error decreases, which should also be examined in future.

Furthermore, using the utilization scenario (Fig.5.(a)) for the proposed pipeline, a material database can be constructed in an online manner while the production carries on press brake. This ability eliminates tedious offline calibration sessions and decreases the overall production time extensively while limiting the amount of scrap material.

Table 2. Results of the proposed algorithm pipeline

Type of Features	HNs	Input Feature vectors	Cumulative Training Time (s) – MAE (nm) – ME (nm)		
			ST37-2	ST41	ST52-3
Linear	10	$[x_1,\ldots,x_{12}]_{1\times12}$	4.7 – 3320 – 4212	4.3 – 3620 – 4912	5.1 – 3710 – 3997
	25		5.0 – 2810 – 4102	4.8 – 3112 – 4803	5.2 – 2912 – 4239
	50		5.2 – 2722 – 3921	5.4 – 3001 – 4395	5.7 – 2831 – 4571
2nd order polynomial	10	$[x_1,\ldots,x_{12}, x_1^2,\ldots,x_{12}^2, x_1x_2,\ldots,x_{11}x_{12}]_{1\times90}$	12.1 – 532 – 692	12.3 – 501 – 718	12.8 – 485 – 578
	25		17.6 – 312 – 452	17.1 – 331 – 427	16.2 – 299 – 452
	50		21.7 – 291 – 397	20.2 – 278 – 360	19.5 – 264 – 389
3rd order polynomial	10	$[x_1,\ldots, x_1^2,\ldots, x_1^3,\ldots, x_1x_2,\ldots,x_1x_2x_3,\ldots]_{1\times322}$	42.9 – 196 – 304	66.4 – 202 – 361	38.4 – 125 – 277
	25		75.9 – 53 – 138	81.1 – 77 – 151	62.2 – 47 – 101
	50		142.9 – 42 – 111	163.7 – 40 – 98	127.5 – 36 – 87

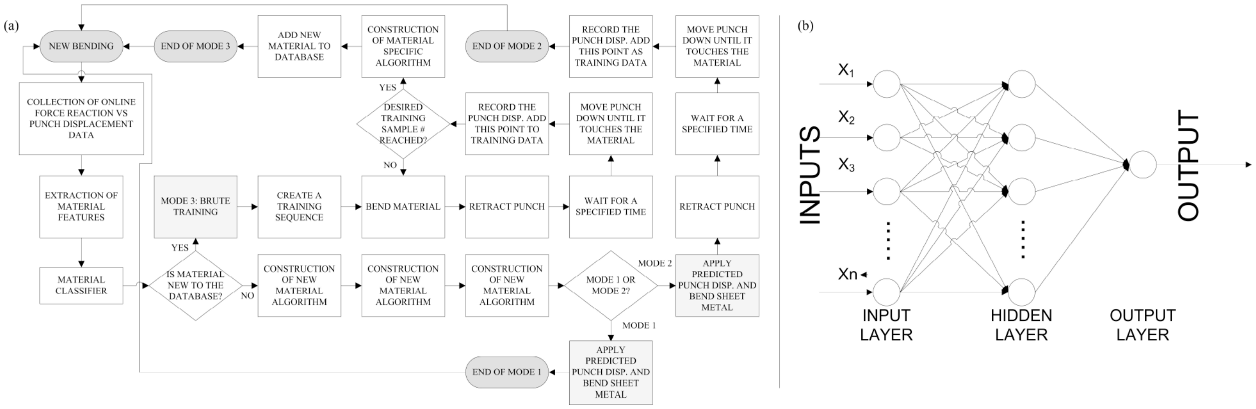

Fig. 5.(a) Utilization of intelligent algorithm pipeline on press brake system; (b) Basic neural network structure

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