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Deep Learning-based 3D Printer Fault Diagnosis

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Article

Additive manufacturing, also familiar as 3D printing , is a manufacturing method based on material deposition and its preserving layer by layer which can be performed via various methods and materials . As it has many virtues compared to conventional manufacturing methods, the applications of the 3D printing have rapidly increased . The basic advantage of the 3D printing is the capability to build almost any geometric . On the other side, one of the main drawbacks is its lesser dimensional accuracy, as the precision of the 3D printing is affected by various factors which have limited its continuous development . One of the significant factor is the mechanical transmission of the 3D printer. Hence it is needed to track the transmission condition of the 3D printer despite being possessing precision components . 3D printing is a rapid prototyping with broad application prospects additive manufacturing technology, which is based on digital model files. The layer printing method is used to manufacture objects or products . According to the transmission structure, common 3D printers can be divided into parallel 3D printers and serial 3D printers . There are two types of printers, and the tandem mechanism can provide a large motion space, and the parallel mechanism 3D printer has a compact, the advantages of light weight, good rigidity and high transmission precision . No matter what kind of transmission mechanism 3D printer is used, after a period of time, its transmission accuracy may deteriorate. Parallel arm take the 3D printer as an example, the universal ball bearing and synchronous transmission on the transmission chain moving belts may cause transmission clearance due to wear or aging, thus affect the quality of the final printed product. Although it affects 3D printing products. There are many factors of quality, but the accuracy of mechanical transmission is the most important factor, one of the primes . Therefore, fault diagnosis for 3D printing is a guarantee important measures for printing quality and accuracy. The implementation process of mechanical fault diagnosis includes at least two aspects. The first aspect is to choose effective operating parameters. Existing research shows that vibration, temperature, sound, current, humidity lubricating oil parameters can be used to reflect the health or failure of the mechanical system obstacle state . In order to effectively obtain the mechanical state parameters, people often install a variety of different sensors at appropriate locations in the system to collect fault-sensitive process signals. In addition to collecting valid sensor signals, another important factor is the fault diagnosis algorithm. Although to fault sensitive sensors can detect weaker faults, but suitable fault diagnosis algorithm can improve the sensor to a certain extent diagnostic capabilities. In order to deal with the large number of monitoring generated by a large number of sensors, according to research, researchers use sensor signals in the time domain, frequency domain, time-frequency domains or other nonlinear domains , using regression, classification, fault diagnosis was carried out by different means such as clustering . There are existing fault diagnosis methods in typical mechanical systems (such as gears, shafts and other rotating machinery have been successfully applied . Common with these compared to its mechanical system, 3D printers are compact in structure and complex in motion. Moreover, commercial 3D printers in the market are sensitive to cost and highly sensitive. Degree of fault diagnosis sensors are expensive and difficult to market, this all bring challenges to the practical diagnosis of 3D printers with market value war. In order to effectively monitor the fault, it was proposed in the early stage, an attitude sensor is installed at the end of the moving chain (that is, the print head). Monitor the posture of the print head to diagnose the 3D printing status . Although using industrial-grade attitude sensors can effectively identify printing failures, but its hardware cost is still relatively high. To troubleshoot the 3D printer is more commercially useful, this study proposes the use of consumer grade 3D printing status signal to collect the attitude sensor. Consumer grade attitude sensors have been widely used in consumer electronics such as mobile phones application, the cost of which is completely within the acceptable range of commercial 3D printers inside. However, the disadvantage of low-cost sensors is their fault diagnosis. The cutoff sensitivity is low. In order to make up for the shortage of consumergrade attitude sensors. Research further proposes to use better fault diagnosis algorithms to improve hardware, the comprehensive performance of the system. Deep learning is a fault diagnosis method based on big data, its effectiveness has been obtained by many big data researchers in the field of fault diagnosis verification . The core of deep learning is composed of two stages of learning , that is, unsupervised training (pre-training) and supervised learning (fine-tuning). This two-stage IET Research . The Institution of Engineering and Technology 2015 1 learning method effectively provides improved deep learning performance for big data. Based on deep learning, in the fault diagnosis method, the appropriate deep network structure and the appropriate points classifiers have always been the focus of research . In view of this, we are subject to two-stage deep learning methods including pre-training and fine-tuning inspired by the method, a sub-optimal deep learning network is proposed to further adopt use two-stage classification (pre-classifying and fine-classifying), On the one hand, it adaptively determines a sub-optimal network with better performance structure, on the other hand to further enhance the device status of deep learning networks state classification performance. Make up for consumer-grade posture through sub-optimal network deep learning. The hardware of the state sensor is insufficient. Take the parallel arm 3D printer as an example inspection and testing to lay the groundwork for improving the commercial applicability of 3D printing fault diagnosis set the foundation. The rest of the paper is organized as follows:, parallel arm 3D printing attitude monitoring is introduced. The, a deep learning method for suboptimal networks is described, with pre-training and fine-tuning of deep Boltzmann machines. The experimental method is taken. Results and discussions are drawn in printer. Finally, the conclusions are made . 2 Parallel arm 3D printing attitude monitoring The driving diagram of the parallel arm 3D printer asshows that within the outer frame of the printer, three driving motors drive three synchronous belts independently in triangular structure.One slider is mounted on each of the synchronizing strips, and two links are attached to each slider. Three motors drive one end of six connecting rods to run through three synchronous belts and three sliders. The other ends of the six connecting rods are respectively connected with the printing head in a triangle, and the connection is realized by a universal ball bearing which is arranged at the two ends of each connecting rod.In this way, the movement of the three motors enables the synthesis of the print head in a three dimensional space divided into the outer frame. By spraying the printing material during the movement process, the workpiece product of the three dimensional entity can be printed on the workpiece table. Outer Frame One Sync band Slide Blocks Bearing Connecting Rod Print Head Work : Schematic diagram of parallel arm 3D printing transmission. The parallel arm 3D printing transmission mechanism belongs to a kind of a typical 3-P[2-SS] mechanism is calculated as follows. A = 6(k − m − 1) +Xm i=1 ni (1) In the formula, A is the number of degrees of freedom, k is the number of components including the outer frame, m is the number of kinematic pairs, ni denotes the degrees of freedom of the first kinematic pair number., k=11 (1 outer frame, 3 sliders, 6 1 link, 1 print head), m = 15 (3 moving pairs and 12 balls the degree of freedom of the moving pair is 1 and the degree of freedom of the spherical pair is 3). This in addition, the degrees of freedom of the link are local degrees of freedom. The final output motion of the printhead has no effect.As a result, The parameter substitution formula and subtracting the local degrees of freedom of six connecting rods can calculate the degrees of freedom A = 3 of the parallel arm 3D printer. Even for 3D printers designed and manufactured with complete precision, After a period of time, the transmission performance will be degraded. Through simplification the mechanism analysis shows that if the component itself is not damaged, then the mechanical transmission performance degradation mainly comes from the relaxation of the synchronous belt. The result will be in the end of the transmission chain. The end is reflected on the printhead.Therefore, by monitoring the print head the motion state can indirectly reflect the fault diagnosis of the entire transmission chain. To this end, the attitude sensor was used to monitor the print head motion posture. Attitude sensor is a three dimensional motion attitude measurement system, embedded widely in mobile phones, aerial models, drones, robots, mechanical platforms, vehicle, ship, ground and underwater equipment to measure three dimensional posture state and orientation . Attitude sensor is based on MEMS technology. Its output includes a 3-axis gyroscope, a 3-axis accelerometer, and a 3-axis electrical motion sensors such as a compass. In theory, a 3- axis gyroscope can be used. The instrument signal generates attitude angle, which is calculated as follows φi = (ωi − ωb)dt + φi−1 In the formula, φi represents the attitude angle measured at time t = i. The components of x, y and z are α, β, γ, respectively. ωi is a gyro, the output angular velocity of the instrument, ωb , is the angular velocity deviation. However, formula there is a cumulative error in the calculation, so the 3-axis acceleration is further utilized, the result obtained by the formula is calculated and corrected by the meter and the 3-axis electronic compass. Three-axis posture calculated with 3-axis accelerometer and 3-axis electronic compass. The angle of state is as follows: α = arctan ax q a 2 y + a 2 z (3) β = arctan ay p a 2 x + a 2 z ! (4) γ = arctan my cos β + mx sin β sin α − mz sin β cos α mx cos α + mz sin α (5) In the formula, ax, ay, az are the accelerations of the three axes of x, y, and z, respectively; mx, my, and mz are 3-axis electronic compass outputs, respectively. Using the above monitoring principles, attitude sensors can monitor a total of 3D print, the 12 motion signals at the end of the drive chain. Among them, 3-axes, the attitude angle data is calculated second-hand data, so in research, we select only the original signals of the remaining nine channels, S(t)= {s1(t), s2(t), . . . , s9(t)}. Compatible with military grade or industrial grade attitude sensors. In contrast, consumer-grade attitude sensors are inexpensive and have large-scale commercial. The advantage of low cost for industrial applications, but its disadvantage is that the monitoring accuracy is low. Therefore, this study proposes a deep learning method for suboptimal networks. Better fault diagnosis algorithm to compensate for the monitoring sensor hardware the lack of degrees. IET Research Journals, pp. 1–7 2 © The Institution of Engineering and Technology 2015 3 A Deep Learning Method for Suboptimal Networks 3.1 Pre-training and fine-tuning of deep Boltzmann machines Deep learning networks generally use layer-by-layer, unsupervised pre-training and super fine-tuning of the whole network combining learning strategies. With this learning strategy, the various features are available in a higher-level network. When applied to device status classification, it can be at the highest level of the network get better results in the classifier. The deep Boltzmann machine is a typical deep learning network, In the study, the deep Boltzmann machine was used as an example to construct the network structure. The standard deep Boltzmann machine consists of a series of random binary neurons connected by symmetric coupling, the network structure includes 1 layer v and L hidden layers h (1) , ..., h (l) , ..., h (L) . In the network the energy E transmitted in n v, h(1), . . . , h(L) o is defined as [20]. E(v, h(1), ..., h(L) |θ) = − X Nv i=1 X N1 j=1 Wijvih (1) j − X Nv i=1 bivi− X Nv i=1 X Nl j=1 b (l) j h (l) j − L X−1 i=1 X Nl j=1 N Xl+1 k=1 W (l) jk h (l) j h (l+1) k (6) In the formula, θ = {W, b} is the network parameter, Wij is the connection weight between the first visible neuron and the seventh hidden neuron, bi is the first deviation term, Nv is the number of visible neurons, Nl is the number of neurons in the l th hidden layer. Since the standard deep Boltzmann machine can only deal with binary (0 or 1) neurons, when it is applied to fault diagnosis, appropriate modifications are needed to deal with real-valued signals. To this end, the standard deviation σ is introduced in the visible layer, and the formula (6) can be rewritten as [22] E(v, h(1), ..., h(L) |θ) = − X Nv i=1 X N1 j=1 Wijvih (1) j /σ2 i + X Nv i=1 2(vi − bi) 2 /σ2 i − X Nv i=1 X Nl j=1 b (l) j h (l) j − L X−1 i=1 X Nl j=1 N Xl+1 k=1 W (l) jk h (l) j h (l+1) k (7) The joint distribution between visible and hidden layers can be calculated as follows p(v, n h (l) o |θ) = 1 z(θ) exp − E(v, n h (l) o |θ) ! (8) In the formula, Z(θ) represents the regularization constant related to the network parameter, θ. The Boltzmann machine energy function expressed by the above formula is applied to calculate the conditional probability distribution of the first visible layer neuron. p(vi |h (1), θ) = N vi | X N1 j=1 h (1) j Wij + bi , σ 2 i ! (9) In the formula, N(.|μ, σ2) represents the probability density of the normal distribution, and its mean is μ. The standard deviation is σ. Using the same method, different hidden layers can be deduced. The conditional probability distribution of neurons is p(h (l) j |h (l−1), h(l+1), θ) = s N Xl−1 i=1 h (l−1) i W (l−1) ij + N Xl+1 k=1 h (l+1) k W (l) jk + b (l) j ! (10) In the formula, s(.) is a Sigmoid function. There are two special cases in the formula: for the last hidden layer (i.e. l=L), NL + 1 = 0; For the first hidden layer (i.e. l=1), the parameter in the above formula is set to h (l−1) = v N Xl−1 i=1 h (l−1) i W (l−1) ij = X Nv i=1 viWij/σ2 i (11) The Boltzmann machine network described by the above formula does not automatically possess classification functionality. When it is applied to a device state classification problem, one Softmax classifier is usually added at the top of the top layer. The top layer of the network is the input of the Softmax classifier a, its i Elements can be represented as ai = N XL−1 j=1 h (L−1) j W (L−1) ij (12) For a given NL neuron, the classifier assigns it to class c. The probability that the result will be attributed to Class i is recorded as pi = exp(ai) PNL i=1 exp(ai) X NL i=1 pi = 1 With this method, an input signal can be classified to have a maximum, the category i of probability is expressed as follows ∧ i = argi max pi = argi max ai (14) In deep Boltzmann machines, its learning process is divided into pretraining and fine tuning. The first stage is the pre-training stage. A preliminary study of network parameters by layer-by-layer, unsupervised Learning Xi . In the second phase, a top-down supervised learning approach is adopted. It's called fine tuning. At this stage, the output layer of the network is a multilayer perceptron connected by Sigmoid function is replaced. Then, the network parameters are refined by the back propagation algorithm. Pretrain stage, using unsupervised learning and only need to consider the current layer parameters. In the fine tuning stage, supervised learning is adopted and considered. Parameter optimization of the entire network structure. There are still two Zman Machines in 3D printing fault diagnosis Problem: First, how to determine a better network structure, including the network layer number of neurons in each layer, etc.; second, how to further the performance of the classifier is upgraded. To this end, we propose a new method based on pre-classification and fine classification strategy. Sub-optimal network structure based on pre-classification and fine classification The concept of deep Learning in suboptimal networks-based on integrated parameter adaptation. This paper introduces a new method of RBM (Restricted Boltzmann Machine). In this paper, the parameter adaptive adjustment concept is applied to pre-classification and precision. A sub-optimal Boltzmann machine network combining IET Research Journals, pp. 1–7 The Institution of Engineering and Technology 2015 3 fine classification. Making Deep Bohr the learning sample X of the Zmann machine consists of two parts. X|C = {X1|C1 , X2|C2 } (15) In the formula, C is the classification label corresponding to the sample, X1 and X2 are, respectively, data set 1 (for training models) and number in training set samples data set 2 (for testing the model) with the corresponding classification label C1 and C2. For the l th hidden layer h(l), it is assumed that there exists a mapping matrix L×c, AR, making the hidden layer state phase with the training set label information C1 corresponding, that is h (l)A = C1 (16) The transformation matrix h (l)T is multiplied by h (l) at the same time on both sides of the above formula. A = (h (l)T h (l)) −1 h (l)T C1 For the test sample X2, according to the network parameters θ = {W, b}, To obtain the output P of the hidden layer. Combine the hidden layer expressed by the above formula the mapping matrix between the label information and the test sample on the label as ∧ C2 = P|X2 A (18) For the test sample, the error between the theoretical label and the actual label. The rate η can be calculated as follows η = PN i=1 ∧ C2 6= C2 N (19) In the formula, N is the total number of test samples. By controlling the error rate η size, the number of neurons in the hidden layer can be corrected to obtain a better the number of neurons. In theory, only when η = 0, the hidden layer can reach to the optimal structure. But this is actually unrealistic, because most the deep learning computing resources corresponding to the excellent network consume too much, therefore, by appropriately controlling the error rate η (set to 0.1 in this study, it is the same when considering the calculation efficiency and the empirical parameters of recognition accuracy), we can get get the deep learning network parameters with sub-optimal structure. It should be noted that the adaptive adjustment of the suboptimal network structure has been the process is essentially a preclassifying process. In this process, through supervised learning of classification labels, respectively optimize the structure of the Boltzmann machine network layer by layer. Therefore, the adjustment is suboptimal, the pre-classification process of network structure and the pre-training of deep learning. The (Pre-training) process is similar in concept, both are optimizing layer by layer can save computing resources. But in terms of means of realization, the two are different. Pre-training uses unsupervised learning, while pre-score the class uses supervised learning. The pre-classification process can optimize the network structure to a certain extent, the suboptimal network structure is obtained by controlling the size of the error rate η. But, the effect of device status classification also depends on the performance of the classifier. Often, the deep learning process, fine adjustment and final classification process multilayer perceptrons use Softmax classifiers, the reason is in the reverse error transmission process of the classifier, the absolute classification result. The magnitude of the value represents the probability of belonging to the category, which in theory belongs to an approximate linear classification expression. Support vector machine (SVM) uses nonlinear error loss function. Many researchers have used support vector machines instead of multi-layer perceptrons to improve classification accuracy . In addition to the error loss function of Softmax used in the adjustment process, multi-class support vector machines are used as fine classifiers. When using support vectors, the machine is finely classified, let equation (12) be its input Xn, and equation would be output Yn, set category Yn as a binary number category, then support vector machine classification. It is described by the following optimization problem [23] minw,ζn 1 2 w T w + C X N n=1 ζn s.t. wT xnτn ≥ 1 − ζn ζn ≥ 0; n = 1, 2, 3, 4, ..., N (20) In the formula, τn − {1, 1}, ζn is the n th slack variable, C is the penalty function number. The above formula can be expressed as the following unconstrained L2 norm form minw 1 2 w T w + C X N n=1 max(1 − w T xnτn, 0)2 (21) By solving the above formula, the support vector machine calculates the corresponding class ∧ i = argτ max(w T x)τ Based on the above methods, the standard can be constructed by using support vector machine. However, when applied to troubleshooting, due to 3D different printer fault locations may result in different fault classes. To solve this problem, a one-to-many (OAA) strategy is generally used I failure modes. To this end, I branches are trained independently The output of the first support vector machine is ai(x) = w T x (23) Accordingly, for the multi-classification problem, formula can be modified ∧ i = argi max ai(x) What needs to be explained is the fine classification of deep learning for suboptimal networks, two different classification .

Biography:

Vishal Kumar is a professor in Delhi University, and studied in University of BPUT, India. In 2014, he also joined the Institute Of Integrated Nanoscience and left in 2017.

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