Regularization-based Continual Learning for Anomaly Detection in Discrete Manufacturing

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Abstract

The early and robust detection of anomalies occurring in discrete manufacturing processes allows operators to prevent harm, e.g. defects in production machinery or products. While current approaches for data-driven anomaly detection provide good results on the exact processes they were trained on, they often lack the ability to flexibly adapt to changes, e.g. in products. Continual learning promises such flexibility, allowing for an automatic adaption of previously learnt knowledge to new tasks. Therefore, this article discusses different continual learning approaches from the group of regularization strategies, which are implemented, evaluated and compared based on a real industrial metal forming dataset.

Keywords: Anomaly Detection; Continual Learning; Deep Learning; Discrete Manufacturing; Elastic Weight Consolidation; Industrial Transfer Learning; Learning Without Forgetting; Regularization Strategies; Synaptic Intelligence

1. Introduction

Anomalies are a potential problem in all automated systems because they pose a challenge to any control software: By definition, they are what is not addressed by conventional rule or model based automation, and even in data-driven systems, handling them is difficult because they might occur unexpectedly and can differ considerably from any previous occurrence [1, 2]. However, simply ignoring anomalies can be detrimental with consequences ranging from inefficiencies [3] to complete failure [4], possibly harming workers or users [5].

A first step in anomaly handling is anomaly detection. Here, a shift from conventional, static methods towards deep learning based, dynamic approaches could be witnessed in recent years [1, 2]. However, even using those, data scarcity and high process dynamics remain challenging [6].

Mitigation could be provided by knowledge transfer between detection algorithms, bridging over gaps between different smaller datasets or various states of a process. Such a transfer could be realized using regularization-based continual learning approaches, which allow sequential learning of similar tasks without overwriting previously acquired knowledge [6].

Objective: In this article, the feasibility of different regularization approaches towards solving sequential learning problems is analyzed using a time series dataset taken from a discrete manufacturing process.

Structure: In chapter 2, related work on the topics of anomaly detection and regularization-based continual learning is presented. From there, a methodology is derived in chapter 3. Chapter 4 introduces a dataset and describes experiments conducted on that dataset as well as their results. Finally, chapter 5 draws a conclusion and gives an outlook.

2. Related work

2.1. Anomaly detection

Anomalies are a deviation from the rule or an irregularity that is not considered to be a part of the normal, intended
system behavior. Anomalous dynamics are mostly unknown and occur inadvertently, lead to instabilities and are therefore drivers of increased inefficiencies and system errors [1, 2].

In literature, there are usually three different types of anomalies differentiated:

- **Point anomalies** are characterized by a single data instance being considered anomalous. They are usually the easiest to detect and have been subject to extensive research [1, 2].

- **Collective anomalies** are characterized by a series of data instances being considered anomalous as a group, although not each individual data instance needs to be anomalous. This necessarily requires relations between individual data instances, such as their sequence in time series data [1, 2].

- **Contextual anomalies** are characterized by data being anomalous in specific, separately defined contexts only. This necessarily requires contextual attributes describing the data instances’ context [1, 2].

Anomaly detection used to rely upon statistical, classification-based, clustering-based and information theoretic approaches. The common ground of those approaches is the fact that they aim to detect anomalies based on static, time-invariant models. However, many anomalies, especially collective and contextual ones, are dynamic and time-variant, calling for different approaches [2].

In recent years, deep learning based anomaly detection has started to fill this gap. Especially recurrent neural networks, such as long short-term memory (LSTM) and autoencoders (AE), have shown promising results:

In [3], a stacked AE with interconnected gated recurrent units (GRU) for short-term and LSTM for long-term memory is used to detect anomalies as well as to predict the process outputs. The algorithm uniquely performs those different tasks simultaneously on a dataset collected from a care robot tasked with feeding different people.

In [4], LSTM are combined with exponentially weighted moving average (EWMA) in order to significantly increase efficiency on contextual anomaly detection. This is demonstrated on a dataset collected from two simulated industrial robotic manipulators collaborating.

Although these examples highlight the suitability of deep learning based approaches towards solving real-life anomaly detection problems from the industrial domain, they still rely on large datasets in order to be trained. This limits their widespread, practical applicability.

**2.2. Regularization-based continual learning**

In the field of machine learning, the term ‘continual learning’ refers to the transfer of knowledge and skills from one or more source tasks to a target task in order to train a deep learning algorithm capable of solving both, source and target tasks [7, 8]. In the manufacturing domain, this can facilitate learning across several smaller, less homogenous datasets [6], mitigating two key problems hindering a more widespread utilization of machine learning [7]:

- Because of only small numbers of identical industrial machinery, high levels of data protection and little cooperation between different organizations, datasets sufficiently large and diverse for successful training are difficult to acquire [9].

- Because of a growing need for frequent reconfigurations [10], changing processes and dynamic environments, datasets once acquired only provide short-term representations of the problem space necessitating continuous data collection and retraining of algorithms [11].

Continual learning approaches are commonly divided into three categories: architectural, rehearsal and regularization approaches [12] (see Fig. 1). For the mitigation of the two problems described above, one of those is more promising than the other two: Whereas rehearsal approaches still rely on sharing of at least some data and architectural approaches strive only on more loosely related tasks, regularization approaches using altered loss functions in order to solve more closely related tasks appear best suited. Regularization strategies are modelled after synaptic consolidation in the brain, slowing down the change of certain weights depending on their importance on previously learned tasks, thereby selectively reducing the network’s plasticity.

Four specific implementations of regularization strategies are commonly included in comparative analyses [12–14]:

- **Elastic weight consolidation** (EWC) is based on the idea [15] that more than one set of weights $\theta$ represents a possible solution $\theta_A$ of a task $A$, so that a solution $\theta_{AB}$ can be found that solves both tasks $A$ and $B$ [16]. This is achieved by adding a penalty to the loss function (see Eq. 1): $L_C(\theta_{ABC})$ is the (conventional) loss for task $C$ on a set of weights $\theta_{ABC}$ capable to solve all tasks $A$, $B$ and $C$, $\lambda$ defines the importance of old tasks compared to the new one, $F$ is the diagonal of the Fisher information matrix and $i$ labels each individual parameter.

![Fig. 1. Venn diagram of some of the most popular continual learning strategies based upon [12]](image)
\[ L(\theta_{ABC}) = L_C(\theta_{ABC}) + \lambda \cdot \sum_i [F_{A,i}(\theta_{ABC,i} - \theta_{A,i}^*)^2 + F_{B,i}(\theta_{ABC,i} - \theta_{B,i}^*)^2] \]  

**Online EWC** expands on this idea, but shifts attention from older to newer tasks by not relying on Fisher information matrices for every task but on only one for all tasks combined [17]. This reduces Eq. 1 to Eq. 2:

\[ L(\theta_{ABC}) = L_C(\theta_{ABC}) + \lambda \cdot \sum_i \omega_{A,i}(\theta_{ABC,i} - \theta_{A,i}^*)^2 \]  

**Synaptic intelligence** (SI) relies on a similar idea, but uses an importance measure \( \omega \) that is calculated directly during the stochastic gradient descent as opposed to the Fisher information matrix which needs to be calculated separately [18], leading to Eq. 3:

\[ L(\theta_{ABC}) = L_C(\theta_{ABC}) + \lambda \cdot \sum_i \omega_{A,i}(\theta_{ABC,i} - \theta_{A,i}^*)^2 \]  

**Learning without forgetting** (LwF) uses a slightly different approach: Differentiating between global weights \( \theta_o \), weights specific to the old task(s) \( \theta_n \) and those for the new task \( \theta_n^* \), the algorithm tries to minimize both, the loss on the old task using \( (\theta_o, \theta_n) \) and on the new task using \( (\theta_o, \theta_n^*) \). The loss on the old task is brought into the training of the new task by using the Hessian matrix, a representation of individual weights importance for the overall result – similar to EWC’s Fisher information matrix or SI’s importance measure [19]. This yields Eq. 4:

\[ \theta_o^*, \theta_n^*, \theta_n^* \leftarrow \text{argmin} \left( \lambda_o L_o(Y_o, \hat{Y}_o) + L_n(Y_n, \hat{Y}_n) + \frac{1}{\omega} R(\theta_o^*, \theta_n^*, \theta_n^*) \right) \]  

Although the aforementioned regularization approaches displayed good results on different general evaluation datasets [13, 14], there are to the authors’ knowledge no publications on their performance in the industrial domain – with one exception being EWC for fault prediction [6]. This article therefore aims to provide a first comparative analysis of those approaches on time series data taken from an actual manufacturing process.

### 3. Methodology

Based upon the good performance of recurrent neural networks described in chapter 2.1 combined with the desire to create a simple algorithm requiring neither vast computing resources nor extensive optimization, a multilayer LSTM-approach was chosen as base algorithm. This allows a focus on the different regularization methods and their respective performance. However, one must keep in mind that using a different, more sophisticated base algorithm might very well further increase the overall performance.

For this base algorithm, an input layer of dimension 3000 is connected to stacked LSTM-layers which lead to a two-node output layer (see Fig. 2).

Upon this base algorithm, the different regularization approaches are implemented. Because they only alter the respective loss functions, no changes to the base algorithm’s network structure were necessary.

### 4. Experiments

In this chapter, a dataset collected from a discrete manufacturing process is introduced. The anomaly detection problem represented by the dataset can be classified as belonging to incremental domain learning [20]. Using this dataset, different experiments are conducted testing the previously described regularization approaches.

All experiments were conducted on a computer featuring an AMD Ryzen Threadripper 2920X CPU and a NVIDIA GeForce RTX 2080 8 GB GPU running Ubuntu 20.04. The learning framework used was PyTorch 1.6 under Python 3.6.

| Table 1: Hyperparameters used for the different regularization-based continual learning algorithms |
| Parameter | Value |
| Learning rate | 0.001 |
| Batch size | 100 |
| Number of hidden layers | 2 |
| Number of nodes per hidden layer | 200 |
| \( \lambda_{ewc} \) | 1,000,000 |
| \( \gamma_{ewc} \) | 10 |
| \( \epsilon_{SI} \) | 300 |
| \( T_{lwf} \) | 10 |
| \( R_{lwf} \) | 1 |
4.1. Experimental dataset

The experiments were conducted using the subset of a very large industrial metal forming dataset collected on a hydraulic press. It consists of data from eight pumps applying pressure on a shared oil reservoir. Due to this setup, anomalous behavior of one pump is compensated by other pumps (see Fig. 3). This hides such behavior from the operator, because initially no problems occur. However, the other pumps experience increased wear, which makes an early detection of the described anomalous behavior desirable.

The challenge is further increased by frequent alterations of the production process, either by improvements such as new molds or changes of the manufactured product. Every alteration causes a change of the process’ characteristics, which require anomaly detection algorithms to be retrained.

In the dataset used in this study, labeled pressure data from the production of fifteen different products each being produced hundreds of times are included.

4.2. Regularization-based continual learning anomaly detection on a sequence of five tasks

A first set of experiments was conducted randomly drawing twenty sequences of five tasks, i.e. five different products, and using all four approaches to classify normal or anomalous pump behavior. For baseline comparison, an algorithm without any regularization enhancement was used. After training on one task, the algorithm was validated on all tasks before training switched to the next task.

Without regularization (see Fig. 4, top left diagram), the accuracy on the task being trained on is about 0.92, whereas on the others it is between 0.5 and 0.7. The rapid decline of accuracy on one task after training switches to the next task, commonly called catastrophic forgetting [21], is easy to distinguish. Overall, even after training on all tasks, the algorithm is clearly not capable of solving all of them sufficiently well, underlining the need for a different approach.

When EWC is used (see Fig. 4, top middle diagram), the accuracy on the task being trained on is slightly declining from 0.92 for task 1 to 0.9 for task 5. Prior to being trained on, a task’s accuracy lies between 0.5 and 0.65. After training switches from on task to the next, the prior tasks’ accuracies decline – although considerably less than without any regularization.

When Online EWC is used (see Fig. 4, top right diagram), the accuracy on the task being trained on is considerably declining from 0.92 for task 1 to about 0.8 for task 5. Prior to being trained on, a task’s accuracy lies between 0.5 and 0.65. After training switches from on task to the next, the prior task’s accuracy declines, but stays somewhat constant following subsequent switches. This causes the final accuracies of all tasks except the last being trained on to be significantly higher than without any regularization or using EWC.

When LwF is used (see Fig. 4, bottom right diagram), the resulting accuracies resemble that without any regularization with an average offset of about +0.025. This offset is caused by slight accuracy improvements on previously trained on tasks, while the accuracies on the tasks currently being trained are similar.

When SI is used (see Fig. 4, bottom middle diagram), the resulting accuracies also resemble that without any regularization with an increasing average offset of -0.01 for tasks 1 to +0.025 for task 5. This time, the offset is not caused by retained skills.

Comparing the mean accuracies of the different approaches (see Fig. 4, bottom left diagram), no regularization, LwF and SI result in similar curves, distinguishable mainly due to the previously described offsets. Starting at about 0.62 they peak during training on tasks 3 and 4 before slightly declining again. Contrastingly, EWC’s and Online EWC’s accuracies keep on rising throughout the entire training sequence.

Table 2 focusses on the different tasks’ accuracies during the training of task 5: Although it has the overall highest accuracy on task 5, no regularization expectably fares worst regarding the lowest (0.52 for task 2) and the mean accuracies (0.66). LwF and SI perform only marginally better. With only a slightly worse accuracy on task 5 (0.9), EWC has much better

| Approach                        | Best | Mean | Worst |
|---------------------------------|------|------|-------|
| No Regularization               | 0.93 | 0.66 | 0.52  |
| Elastic Weight Consolidation    | 0.9  | 0.77 | 0.67  |
| Online Elastic Weight Consolidation | 0.85 | 0.82 | 0.79  |
| Learning without Forgetting     | 0.92 | 0.68 | 0.57  |
| Synaptic Intelligence           | 0.91 | 0.68 | 0.57  |
Concludingly, Online EWC combines the worst accuracy on task 5 (0.85) with best worst (0.79 for task 4) and mean (0.82) accuracies. Online EWC clearly performs best in learning to solve all five tasks. After having trained on all of them, all tasks’ accuracies are in the vicinity of 0.8. However, the decreasing accuracy on the task being currently trained on raises the question of its performance when more tasks are added to the sequence.

4.3. Regularization-based continual learning anomaly detection on a sequence of eight tasks

A second set of experiments repeats the first set using eight tasks being trained on sequentially instead of five. The key characteristics remain similar: Without regularization (see Fig. 5, top left diagram), the accuracy on the task being trained on is about 0.9 to 0.92, whereas on the others it is between 0.4 and 0.75 with distinct catastrophic forgetting. Again, LwF (see Fig. 5, bottom right diagram) and SI (see Fig. 5, bottom middle diagram) perform slightly better with the notable exceptions of SI’s performance on tasks 4 (+0.05) and 7 (+0.065).

When EWC is used (see Fig. 5, top middle diagram), the accuracy on the task being trained on lies between 0.85 and 0.91 without a clear trend. The effect of catastrophic forgetting is reduced significantly. When Online EWC is used (see Fig. 5, top right diagram), the accuracy on the task being trained on is considerably declining from 0.9 to 0.68. Again, accuracy levels stabilize after initial drops once the respective task is no longer being trained on. However, for the last task, training does not even bring it to the accuracy level of the other tasks after their drop. Therefore, the assumption that the regularization capacity of our implementation is depleted after eight tasks appears to be correct.

The significant differences in mean accuracies between the first five training phases of the second set of experiments (see Fig. 5, bottom left diagram) and the first set of experiments hints towards a strong influence of individual tasks on the overall results despite averaging over twenty randomly created task sequences.

Table 3 gives the different tasks’ accuracies during training of task 8. Compared with Table 2, the absolute accuracies decreased slightly, but the relative order remained without significant changes, leaving online EWC performing best over all eight tasks.

In this paper, the feasibility of different regularization approaches towards solving sequential learning problems in industrial use cases was examined. A time series dataset taken from a discrete manufacturing process was used to evaluate the algorithms.

Our main findings are:

- Regularization approaches improve our base algorithm’s performance compared to no regularization.
- Online elastic weight consolidation outperforms elastic weight consolidation, learning without forgetting and synaptic intelligence.
- The performance of all approaches decreases with the number of tasks to be learnt.

| Approach                    | Best | Mean | Worst |
|-----------------------------|------|------|-------|
| No Regularization           | 0.93 | 0.61 | 0.50  |
| Elastic Weight Consolidation| 0.88 | 0.73 | 0.64  |
| Online Elastic Weight Consolidation | 0.82 | 0.75 | 0.68  |
| Learning without Forgetting | 0.93 | 0.62 | 0.50  |
| Synaptic Intelligence       | 0.88 | 0.62 | 0.54  |
The tasks themselves have a big influence on the learning performance. It remains unclear, whether this only depends on their relative similarity to each other or also on their individual position in the learning sequence.

Future research should carry out hyperparameter optimizations for all approaches, possibly even for different task sequence lengths. Furthermore, the number of randomly created task sequences should be increased in order to reduce the impact of each individual sequence. Additionally, experiments involving other industrial datasets could be of interest.

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