Dynamic Weight Alignment for Temporal Convolutional Neural Networks

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Abstract—In this paper, we propose a method of improving Convolutional Neural Networks (CNN) by determining the optimal alignment of weights and inputs using dynamic programming. Conventional CNNs convolve learnable shared weights, or filters, across the input data. These filters use an inner product to linearly match the shared weights to a window of the input. However, it is possible that there exists a more optimal alignment of weights. Thus, we propose the use of Dynamic Time Warping (DTW) to dynamically align the weights to optimized input elements. This dynamic alignment is especially useful for time series recognition due to the complexities with temporal distortions, such as varying rates and sequence lengths. We demonstrate the effectiveness of the proposed architecture on the Unipen online handwritten digit and character datasets, the UCI Spoken Arabic Digit dataset, and the UCI Activities of Daily Life dataset.

I. INTRODUCTION

Neural networks and perceptron learning models have become a powerful tool in machine learning and pattern recognition. Early models were introduced in the 1970s, but recently have achieved state-of-the-art results due to improvements in data availability and computational power [1]. Convolutional Neural Networks (CNN) [2] in particular have achieved the state-of-the-art results in many areas of image recognition, such as offline handwritten digit recognition [3], text digit recognition [4], [5], and object recognition [6]–[8].

In addition to the image domain, CNN models have been used for time series patterns. A predecessor to CNNs, Time Delay Neural Networks (TDNN) [9], [10] used time-delay windows similar to the filters of CNNs. CNNs were also used to classify time series by embedding the sequences into vectors [11] and matrices [12], [13]. However, most recent successes have been through the use of Recurrent Neural Networks (RNN) [14] and in particular, Long Short-Term Memory (LSTM) networks [15].

Specifically, CNNs use sparsely connected shared weights as a convolution. In this way, the shared weights, or filter, act as a feature extractor and maintains the structural aspects from the input. In particular, these shared weights are linearly aligned to each corresponding window value of the input. However, the linear alignment assumes that each element of the input window correspond directly to each weight of the filter in a one-to-one fashion. It is possible that there is a more optimal alignment of the shared weights and the input values.

We propose a method of finding that alignment using dynamic programming, namely Dynamic Time Warping (DTW) [16]. Figure 1 is an example 5-layer CNN using the proposed weight alignment. DTW estimates the globally minimal distance between two time series patterns by elastically matching elements using dynamic programming along a constrained path on a cost matrix. While DTW is traditionally used just as a distance metric, we exploit the elastic matching byproduct of DTW to align the weights of the filter to the elements of the corresponding receptive field to create more efficient feature extractors for CNNs.

The contribution of this paper is twofold. First, we propose a novel method of aligning weights within the convolutional filters of CNNs by dynamically matching the weights to similar input values. Using the discovered dynamic weight alignment, we create a nonlinear matching to create more effective convolutions. Second, we demonstrate the effectiveness of the proposed method on multiple time series datasets including: Unipen online handwritten digit and character datasets, the UCI Spoken Arabic Digit dataset, and the UCI Activities of Daily Life dataset. We perform a comparative study using a traditional CNN to reveal the benefits of the proposed weight alignment. In addition, we compare the proposed method to other state-of-the-art methods for time series classification.

II. RELATED WORK

Neural networks and perceptron learning methods for time series recognition have been extensively explored in literature.
Many classic models were used for time series forecasting \cite{17,19} where artificial neural networks were provided a sliding window of a discrete signal and were tasked with predicting future time steps. However, these methods learn rigid relationships to temporal features and are susceptible to temporal distortions and shift variance.

TDNNs are classical feed-forward neural networks designed to address shift variance \cite{9} by introducing wider sliding window receptive fields to represent multiple points in time. These windows, or time delays, are passed through learned filters to create subsequent feature map time series. CNNs continue the idea of learned filters permeated across a structural input to the domain of images. However, CNNs have been used for time series recognition by considering the time steps as a dimension for the convolutions. Zheng et al. \cite{11} use CNNs with 1D subsequences created from multivariate time series. There also have been attempts \cite{12,13,20,21} to classify time series patterns by embedding them into 2D matrices for classification by CNN.

There are other notable feedforward network architectures that have been proposed to address the characteristics or features of time series patterns. For instance, MLPs have been applied to wavelet transforms \cite{22} and ARMA(p,q) time series data \cite{18} for forecasting and classification. Spiking neurons \cite{23,24} create sparse representations using brief spikes time series data. WaveNet \cite{25} employs dilated causal convolutional layers to generate audio.

Other than feedforward networks, recurrent models like RNNs and LSTMs have been successful in time series recognition \cite{26,28}. Similar to other models, RNNs are given a sliding window of the input time series. However, unlike feedforward networks, RNNs use recurrent connections and stored hidden states to maintain a dependence on time.

Dynamic neural networks is an emerging field in neural network learning. There are generally two approaches, dynamically embedding trained parameters into a network and using dynamic connections. Dynamic Filter Networks (DFN) \cite{29} use filter-generating networks to produce filters that are dynamically used depending on the input. Klein et al. \cite{30} similarly uses filters that vary depending on the input. Dynamic Convolutional Neural Networks (DCNN) \cite{31} use dynamic k-Max Pooling to simplify CNNs for sentence modeling. Deformable Convolutional Networks \cite{32} use deformable convolutions to relax the constraints of a traditional convolutional window. The distinction between these models and the proposed method is that we use dynamic programming to estimate the optimal weight alignment within convolutions.

DTW-NNs \cite{33} similarly use DTW as a nonlinear inner product for neural networks. The difference between a DTW-NN and the proposed model is that DTW-NN uses a sum of Euclidean distances between a learned prototype sequence and the input. This means that the values of the weights are determined by a distance metric and not directly trained like the method described in this paper. In addition, we implement a CNN with shared weights which means that the output of the node retains temporal qualities instead of a scalar output. This allows for the ability to stack multiple dynamically aligned weight layers to create deep networks.

III. Dynamic Weight Alignment for CNNs

The goal of the proposed method is to exploit dynamic programming to determine the optimal alignment of weights for convolutional layers in CNNs. In this case, we define “optimal” as the globally minimal warping path determined by DTW. In other words, instead of the conventional linear inner product of a convolution, the convolutional filter weights and the input window values are dynamically matched to minimize the difference between similar features of the weights and the input values. Figure 2 demonstrates the difference between a conventional convolutional layer with linear weight alignment and the proposed CNN with dynamic weight alignment.

A. Convolutional Neural Networks

A key feature of CNNs is that they maintain sparse connections that promote local connectivity. Each element of a convolutional node only has a receptive field of a small number of locally neighboring inputs. Besides enforcing local relations, the sparsity of a CNN reduces the number of parameters needed to be calculated and allows for the use of larger input sizes. Parameter sharing further reduces the number of parameters required training a CNN. The idea is that the weights of a convolutional layer are shared for each corresponding output element’s local receptive field. In this way, a forward calculation of a convolutional layer is identical to a convolution operation where the shared weights are the filter and the output is a feature map.

Formally, the feature map $z_j^{(l)}$ of a convolutional layer is defined as:

$$z_j^{(l)} = \sum_{i=0}^{I} w_i^{(l)} a_{i+j}^{(l-1)} + b^{(l)}$$  \hspace{1cm} (1)

for each element $j$, where $l$ is the convolutional layer, $l-1$ is the previous layer, $i$ is the index of the filter, and $I+1$ is the window size. We denote $w_i^{(l)}$, $a_{i+j}^{(l-1)}$, and $b^{(l)}$ as the shared weights, the previous layer activations, and the bias respectively. In other words, $z_j^{(l)}$ is the inner product of the shared weights $w^l$ and each window of the previous layer $a_{i+j}^{(l-1)}$. This inner product linearly matches the weights to the inputs within the window. However, it is plausible that there exist instances where particular weights should be matched with more optimal inputs, for example noisy elements or feature translation and scale variance within the filter.

B. Dynamic Weight Alignment

The conventional inner product of a convolution acts much like a similarity function. Thus, the general idea is to align the weights so that there is a stronger activation to input windows that are similar but only slightly misaligned. To optimize the alignment of weights, we adopt a dynamic programming solution, specifically DTW.
1) **Dynamic Time Warping**: DTW is an asymmetric positive semi-definite similarity function that traditionally used as a distance measure between sequences. It is calculated using dynamic programming to determine the optimal match of elements between two sequences. By matching elements, the sequences are warped in the time dimension to align similar features of the time series. DTW distance has shown to be a successful distance measure for time series recognition [34–36].

DTW finds the total cost over an optimal warping path of a local cost matrix using dynamic programming. Given two discrete time series, sequence $p = p_1, \ldots, p_t, \ldots, p_I$ of length $I$ and sequence $s = s_1, \ldots, s_j, \ldots, s_J$, where $i$ and $j$ are the index of each time step and $p_i$ and $s_j$ are elements at each time step, the DTW-distance is the global summation of local distances between pairwise element matches. Namely, the DTW-distance is denoted as:

$$
\text{DTW}(p, s) = \sum_{(i', j') \in M} ||p_{i'} - s_{j'}||, 
$$

where $(i', j')$ is a pair of matched indices $i'$ and $j'$ corresponding to the original indices $i$ of $p$ and $j$ of $s$, respectively. The set $M$ contains all matched pairs of $i'$ and $j'$. Additionally, the set of matched pairs $M$ can contain repeated and skipped indices of $i$ and $j$ from the original sequences, therefore, $M$ has a non-linear correspondence to $1, \ldots, i, \ldots, I$ and $1, \ldots, j, \ldots, J$. $|| \cdot ||$ is a local distance function between elements.

In the proposed method, we adopt an asymmetric slope constraint which is a modification of the slope constraint proposed by Itakura [37], or the slope constraint defined by the recurrent function:

$$
D(i, j) = ||p_i - s_j|| + \min_{j' \in \{j-1, j, j+1\}} D(i-1, j'), 
$$

where $D(i, j)$ is the cumulative sum at the $i$-th element of $p_i$ and the $j$-th element of $s_j$. The global DTW distance, or the result of the nonlinear inner product, is defined as the value at $D(I, J)$. This constraint ensures that the warping path is monotonic and that the number of matches is always equal to the number of elements in $p$.

2) **Dynamic Weight Alignment with Shared Weights**: The forward pass calculation is done in two steps. First, DTW is calculated between the shared weights of each convolution and the receptive field window of the input using the local distance function $|| \cdot ||$ of Eq. 2 defined as the Euclidean distance. This is possible if we consider the weights of the convolution as the time series $p$ and the window of the input as $s$. The result is a mapping of the shared weights to the input values based on minimizing the $L^2$ distance between sequence elements.

Second, the convolution is calculated used the stored mapping. Namely, we propose using DTW to determine $M_j$ and then calculate the result of the convolution $z_j^{(l)}$:

$$
z_j^{(l)} = \sum_{(i', j') \in M_j} w_i^{(l)} a_j^{(l-1)} + b^{(l)},
$$

where $M_j$ is the set of matched indices $i'$ and $j'$ corresponding to the index $i$ of $w_i^{(l)}$ and the index $j$ in $\{j, \ldots, j + I\}$ of $a_j^{(l-1)}$, respectively. When used in this manner, we create a nonlinear convolutional filter that acts as a feature extractor similar to using shapelets with DTW [35]. In addition, it is important to note that unlike a conventional CNN, the set of matched indices $M_j$ allows for duplicate and skipped values of $w_i^{(l)}$ and $a_j^{(l-1)}$.

The idea is that DTW will match similar features from the filter to the input and skip elements with a very high distance to the weights and perform small translations. Therefore, the process of aligning the weight using DTW is repeated for every stride of the convolution during all forward passes including during training and testing. Consequently, the alignment is only kept for the immediate forward and backward round and recalculated on the fly for subsequent iterations.

Fig. 2. The comparison between a conventional linear convolution (a) and the proposed convolution with dynamic weight alignment (b). Both illustrate 1D convolutions with four weights $w_1, \ldots, w_4$ at stride 1. The layer $l-1$ is the previous layer with elements $a_1, \ldots, a_T$ and layer $l$ is the resulting feature map from the convolution with elements $z_1, \ldots, z_J$. Each dot is the product of the corresponding weight and input and the blue circle is the sum of the products.
C. Backpropagation of Convolutions with Dynamic Weight Alignment

In order to train the network, Stochastic Gradient Descent (SGD) is used to determine the gradients of the weights in respect to the error in order update the weights to minimize the loss. For a CNN, the gradient of the error with respect to the shared weights is the partial derivative:

\[
\frac{\partial C}{\partial w_i^{(l)}} = \sum_j \frac{\partial C}{\partial z_j^{(l)}} \frac{\partial z_j^{(l)}}{\partial w_i^{(l)}},
\]

where \( C \) is the loss function. In a conventional CNN, \( w_i^{(l)} \) has a linear relationship to \( z_j^{(l)} \), thus \( \frac{\partial z_j^{(l)}}{\partial w_i^{(l)}} \) can be calculated simply. However, given the nonlinearity of the weight alignment, the calculation of the gradient is reliant on the matched elements determined by the forward pass in:

\[
\frac{\partial C}{\partial w_i^{(l)}} = \sum_j \frac{\partial C}{\partial z_j^{(l)}} \frac{\partial z_j^{(l)}}{\partial w_i^{(l)}} = \delta^{(l+1)} \sum_{(i',j') \in M_j} a_{j'}^{(l-1)}.
\]

B. Architecture Settings

For the experiment, we implement a five-layer dynamically aligned CNN. The first two hidden layers are convolutional layers with 50 nodes of the proposed dynamically aligned filters. In addition, we use batch normalization [42] on the results of the convolutional layers. The third and fourth layers are fully-connected layers with a hyperbolic tangent \( \tanh \) activation and have 400 and 100 nodes respectively. The final output layer uses softmax with the number of outputs corresponding to the number of classes.

The learning rate used in the experiment used a progressive decay to quickly learn the weight parameters in the beginning and slowly refine them later in the training. The learning rate \( \eta_t \) at iteration \( t \) is defined as \( \eta_t = \frac{\eta_0}{1 + \alpha t} \), where \( \eta_0 \) is the initial learning rate and \( \alpha \) is the decay parameter. For all of the experiments, we use the \( 1/t \) progressive learning rate with a \( \eta_0 = 0.001 \) and \( \alpha = 0.001 \) for the convolutional layers and a static learning rate of 0.0001 between the fully-connected layers.

Given that the experimental datasets are made of sequences of different dimensions, the filters should correspond accordingly. The convolutional filters were of size \( 8 \times 2 \) at stride 2, \( 6 \times 13 \) at stride 2, and \( 12 \times 3 \) at stride 4 for the Unipen datasets, the UCI Arabic dataset, and the UCI ADL dataset, respectively. A stride was used to reduce redundant information and decrease computation time. The filters were initialized using a Gaussian distribution with a minimum value of -0.5 and a maximum of 0.5, within a similar range as the dataset. The experiment uses batch gradient decent with a batch size of 100, 50, and 5 for the three datasets respectively and for 60,000 iterations. The very small batch of 5 used for the ADL dataset was due to the dataset only having 705 patterns total.

C. Comparison Methods

To evaluate the proposed method, we compare the accuracy to comparison methods. We report classification results literature as well as evaluate the datasets on established state-of-the-art neural network methods.

a) Reported baselines: To evaluate the proposed method, we compare the accuracy to current methods from literature. For the online handwritten character evaluations, we compare results from two classical methods, DAG-SVM-GDTW [33] and HMM-CS-DTW [44], and two state-of-the-art neural network methods, DTW-NN [33] and Google [45]. For the spoken Arabic digits, there is one reported neural network solution using a WNN [46] as well as other models using a Tree Distribution model [47] and a Continuous HMM of the second-order derivative MFCC (CHMM w/ \( \Delta(\Delta\text{MFCC}) \)) [48].
For the ADL dataset, we compare our results to the original dataset proposal by Bruno et al. [41] who modeled the ADL accelerometer data using Gaussian Mixture Modeling and Gaussian Mixture Regression (GMM + GMR) and the best results of Kanna et al. [49] who used a Decision Tree.

b) Evaluated baselines.: The evaluated baselines were designed to be direct comparisons for the proposed method. The LSTM is used as the established state-of-the-art neural network method for sequence and time series recognition and a traditional CNN is used as a direct comparison using standard convolutional layers. Both comparative models are provided with the same exact training, test, and validation sets as the proposed method. Furthermore, the evaluated methods use the same batch size and number of iterations as the proposed method for the respective trials. For the LSTM evaluation, an LSTM with two recursive hidden layers, two fully-connected layers, and a softmax output layer was used. The LSTM was set to a forget gate bias of 1.0 and had a static learning rate of 0.001. The second comparative evaluation was using a CNN with the same exact hyperparameters as the proposed method, but with standard convolutional nodes.

D. Results

a) **Unipen 1a, 1b, 1c:** The results of the experiments are shown in Table I. The proposed method achieved a test accuracy of 98.08% for digits, 95.67% for uppercase characters, and 94.83% for lowercase characters after 50,000 iterations of training, surpassing the conventional CNN and the LSTM. Furthermore, the proposed method surpassed all of the comparative methods except for Google with 99.2% for the Unipen 1a trial.

b) **UCI Arabic:** The proposed method had an accuracy of 96.95% for the predefined test set with 2,200 speaker independent MFCC spoken Arabic digits. When comparing the results in Table I, it is noted that the proposed method was outperformed by CHMM w/ $\Delta$(ΔMFCC). Nonetheless, the proposed CNN with dynamically aligned weights performed better than the conventional CNN, the LSTM, and the other reported results. In addition, CHMM w/ $\Delta$(ΔMFCC) is a method tailored to MFCC speech recognition whereas the proposed method works well with other domains.

c) **UCI ADL:** Similar to the other datasets, the results in show that the proposed method improved the accuracy over the conventional CNN with linearly aligned weights, with 85.7% and 84.3% respectively. The result of the proposed CNN with dynamically aligned weights far exceeds the accuracy of the original dataset proposal using GMM + GMR.

V. Discussion

A. Analysis

a) **CNN with dynamically aligned weights versus LSTM.:** In the online handwriting and ADL experiments, the LSTM performed poorly compared to both CNNs. One reason for the limited performance of the LSTM is that each individual element of those datasets do not contain a significant amount of information and the model needs to know how all elements work together to form spacial structures. For example, for large tri-axial accelerometer data, individual long-term dependencies are not as important as the local and global structures whereas CNNs excels. Another reason for the poor performance of the ADL dataset could be the low amount of training data (600 training samples), high amounts of noise, and a high variation of patterns within each class. However, the LSTM did comparatively well on the spoken Arabic digits.

b) **CNN with dynamically aligned weights versus CNN with linearly aligned weights.:** The most important comparison is the conventional CNN with linearly aligned weights against the proposed method with dynamically aligned weights. In addition to the increased accuracy, we can observe from Fig. 3 that compared to the conventional CNN, the proposed method achieves a higher accuracy during all parts of training but especially during the early stages. This indicates that the nonlinear alignment optimizes the use of the weights before the generalization of the CNN converges.

One explanation of the improved accuracy is that aligning the weights to their similar corresponding inputs is more efficient than conventional linear matching. The weights of a convolutional layer learned learned by a CNN act like filter for feature extraction [2]. The purpose of using dynamically
aligned weights is to warp the assignment of weights to their most similar corresponding inputs. In this way, noisy input values can be skipped and normally muted but relevant features are enhanced. This provides a more robust convolution.

Figure 3 is a visualization of the outputs of the convolutional layers from the test set using t-Distributed Stochastic Neighbor Embedding (t-SNE) [50]. t-SNE is an algorithm to visualize high-dimensional data which allows the visualization of the response from the convolutional node for each sample in low-dimensional space. The figure shows that the classes, represented by different colors, are more discriminable with the dynamic weight alignment. Figure 3 (a) is from the test samples using a conventional CNN and it shows that many of the classes are made of multiple small clusters whereas Fig. 3 (b) generally contains larger unified clusters. For example, classes “0”, “6”, and “9” are made of multiple clusters in Fig 3 (a), but are unified in (b). The higher discriminability means that there would be less confusion for the higher layers.

B. Computational Complexity

The drawback to using a dynamic weight alignment would be an increased computational complexity. The computational complexity of a convolutional layer is $O(nx_{h}x_{w}f_{h}f_{w})$, where $n$ is the number of convolutional nodes, $x_{h}$ and $x_{w}$ is the height and width of the input, and $f_{h}$ and $f_{w}$ is the height and width of the filter. The complexity of each DTW calculation is $O(f_{w}^{2})$, which is required for every application of a convolutional filter. Thus, the computational complexity of the convolutional layer with dynamic weight alignment becomes $O(nx_{h}x_{w}f_{h}f_{w})$. With small convolutional filter sizes, this a relatively small increase in complexity compared to the overall network.

Table II shows the average per classification run time for a conventional CNN and the proposed method. The networks were constructed in Python using Numpy with no GPU on a desktop computer with an Intel Xeon 2.6 GHz CPU. Since the increased complexity of the model hinges mostly on the window size and the length of the input sequence, the ADL trial has the most increase in run time. However, these speeds are still run time and can be further optimized with the use of GPUs and deep learning libraries.

VI. CONCLUSION

In this paper, we proposed a novel method of optimizing the weights within a convolutional filter of a CNN through the use of dynamic programming. We implemented DTW as a method of sequence element alignment between the weights of a filter and the inputs of the corresponding receptive field. In this way, the weights of the convolutional layer are aligned to maximize their relationship to the data from the previous layer. Furthermore, we show that the proposed model is able to tackle time series pattern recognition. We evaluated the proposed model on a variety of datasets to reach state-of-the-art results.
Dynamic weight alignment for convolutions of CNNs is a promising area of research. The proposed method can be applied to other CNN-based models such as deep CNNs or fully convolutional networks.

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