1-D Convolutional Neural Networks for Signal Processing Applications

Serkan Kiranyaz[1], Turker Ince[2], Osama Abdeljaber[3], Onur Avci[3], and Moncef Gabbouj[4]
[1] Department of Electrical Engineering, Qatar University, Qatar.
Email: mkiranyaz@qu.edu.qa
[2] Electrical & Electronics Engineering Department, Izmir University of Economics, Turkey.
Email: turker.ince@izmirekonomi.edu.tr
[3] Department of Civil Engineering, Qatar University, Qatar.
Emails: o.abdeljaber@qu.edu.qa and onur.avci@qu.edu.qa
[4] Department of Signal Processing, Tampere University of Technology, Finland;
Email: Moncef.gabbouj@tut.fi

***Abstract*—1D Convolutional Neural Networks (CNNs) have recently become the *state-of-the-art* technique for crucial signal processing applications such as patient-specific ECG classification, structural health monitoring, anomaly detection in power electronics circuitry and motor-fault detection. This is an expected outcome as there are numerous advantages of using an adaptive and compact 1D CNN instead of a conventional (2D) deep counterparts. First of all, compact 1D CNNs can be efficiently trained with a limited dataset of 1D signals while the 2D deep CNNs, besides requiring 1D to 2D data transformation, usually need datasets with massive size, e.g., in the "Big Data" scale in order to prevent the well-known "overfitting" problem. 1D CNNs can directly be applied to the raw signal (e.g., current, voltage, vibration, etc.) without requiring any pre- or post-processing such as feature extraction, selection, dimension reduction, denoising, etc. Furthermore, due to the simple and compact configuration of such adaptive 1D CNNs that perform only linear 1D convolutions (scalar multiplications and additions), a real-time and low-cost hardware implementation is feasible. This paper reviews the major signal processing applications of compact 1D CNNs with a brief theoretical background. We will present their state-of-the-art performances and conclude with focusing on some major properties.**
Keywords – 1-D CNNs, Biomedical Signal Processing, SHM

I. Introduction

Unlike the traditional Artificial Neural Networks (ANNs) Convolutional Neural Networks (CNNs) have the unique ability to fuse feature extraction and classification into a single learning body and thus eliminate the need for such fixed and hand-crafted features. Conventional deep CNNs (i.e. 2D CNNs) have been originally introduced to perform object recognition tasks for 2D signals such as images or video frames. They have recently become the *de-facto* standard for many Computer Vision and Pattern Recognition tasks within large data archives as they achieved the state-of-the-art performances [1]-[3]. However, the utilization of a conventional deep CNN for a 1-D signal processing application naturally requires a proper 1D to 2D conversion. For instance, recently, several researchers have attempted to use deep CNNs for fault diagnosis of bearings [4]-[11]. For this purpose, they have used different conversion techniques to represent the 1D vibration signals in 2D. The most commonly used technique is to directly reshape the vibration signal into an $n \times m$ matrix called "the vibration image" [9]. Another technique was used in [5] where two vibration signals were measured using two accelerometers. After that, Discrete Fourier Transform (DFT) was applied, and then the two transformed signals were concatenated into a matrix which can be fed to a conventional deep CNN. For electrocardiogram (ECG) classification and arrhythmia detection, the common approach is to use power- or log-spectrogram to convert each ECG beat to a 2D image [12], [13]. However, there are certain drawbacks and limitations of using such deep CNNs. To start with it is known that they pose a high computational complexity that requires special hardware especially for training. Hence, 2D CNNs are not suitable for real-time applications on mobile and low-power/low-memory devices. Moreover, proper training of deep CNNs requires a very large training dataset in order to achieve a reasonable generalization capability. This may not be a viable option for many practical 1D signal applications where the labeled data is scarce.

To address these drawbacks, compact 1D CNNs have been recently developed to operate directly and more efficiently on 1D signals. They have achieved the state-of-the-art performance levels in several signal processing applications such as early arrhythmia detection in electrocardiogram (ECG) beats [15]-[17], on-site structural health monitoring [14], [18]-[22], motor fault detection [23] and real-time monitoring of high-power circuitry [24]. Additionally, two recent studies have utilized 1D CNNs for damage detection in bearings [25], [26]. However, in the latter study conducted by Zhang et al. [26], both single and ensemble of deep 1D CNN(s) were created to detect, localize, and quantify bearing faults. The deep configuration of 1D CNN used in this study consisted of 6 large convolutional layers followed by two fully connected layers. Other deep 1D CNN approaches have been recently followed by [27]-[29] for anomaly detection in ECG signals. These deep configurations share the common drawbacks of their 2D counterparts. For example, in [26], several "tricks" were used to improve the generalization performance of the deep CNN such as data augmentation, batch normalization, dropout, majority voting, etc. Another approach to tackle this problem is to use the majority of the dataset for training which may not be feasible at all in many practical applications. In the study [26] more than 96% of the total data is used to train the deep network. Hence the assumption that such a large set of training data will be available may hinder the usage of this method in practice. Therefore, in this study we shall draw the focus particularly on compact 1D CNNs with few hidden layers/neurons, and their applications to some major signal processing applications with the assumption that the labeled data is scarce and personalized or device-specific solutions are required to maximize the detection/identification accuracy.

II. 1D CNN Overview

The conventional 2D CNNs are deep, biologically inspired feed-forward ANNs which constitute a simple model of mammalian visual cortex. Compact 1D CNNs [14]-[17], [18] - [25] are their counterparts that work on 1D signals on those applications which have a limited labeled data and high signal variations acquired from different sources (i.e., patients, devices, motors or circuits). To make the analogy simple two types of layers are proposed in compact 1D CNNs: 1) the so-called "CNN-layers" where both 1D convolutions and sub-sampling (pooling) occur, and 2) Fully-connected layers that are identical to the layers of a typical Multi-layer Perceptron (MLP) and hence called as "MLP-layers". The configuration of a 1D-CNN is determined by the following hyper-parameters:

1) Number of hidden CNN and MLP layers/neurons.
2) Filter (kernel) size in each CNN layer.
3) Subsampling factor in each CNN layer.
4) The choice of pooling and activation operators.

Three consecutive CNN layers of a 1D CNNs are shown in Fig. 1. In this sample illustration, the 1D filter kernels have size 3 and the sub-sampling factor is 2 where the k^{th} neuron in the hidden CNN layer, l, first performs a sequence of convolutions, the sum of which is passed through the activation function, f, followed by the sub-sampling operation. This is basically the predominant difference between 1D and 2D CNNs, where 1D arrays replace 2D matrices for both kernels and feature maps. At the end, the CNN layers process the raw 1D data and "learn to extract" such features that can be used in the classification task performed by the MLP-layers. Therefore, both feature extraction and classification operations are *fused* into one process that can be optimized to maximize the classification performance. This is the main advantage of the 1D CNNs that can also provide a low computational complexity since the only costly operation is a sequence of 1D convolutions that are nothing but linear weighted sums of two 1D arrays. Such a linear operation during both forward and back-propagation can be executed efficiently in parallel.

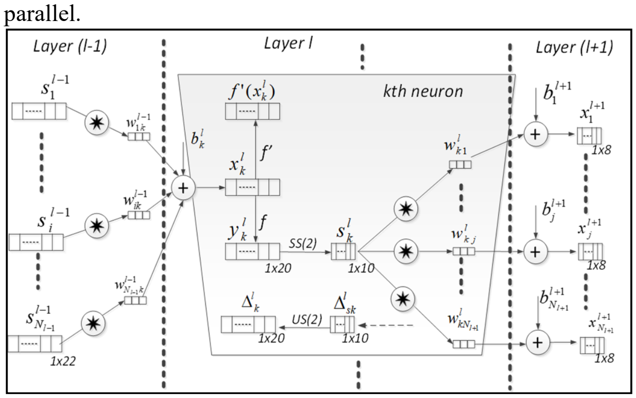

Figure 1: Three consecutive hidden CNN layers of a 1D CNN [17].

This is also an adaptive implementation since the CNN topology will permit the variations in the input layer dimension in such a way that the sub-sampling factor of the output CNN layer is tuned adaptively [3], [14]-[25]. Details regarding forward and back-propagation in CNN layers are covered in Appendix A.

III. Applications of 1D CNNs

There are several application domains where compact 1D CNNs have recently became the *de-facto* standard as they have achieved state-of-the-art performance with minimal computational complexity. Due to the space limitations, in this study we shall cover the following three application domains.

A. Applications on ECG Monitoring

One of the earliest 1D CNN application was on ECG beat identification [16] where a "patient-specific" solution was proposed, i.e., for each arrhythmia patient a dedicated compact 1D CNN was trained by using the patient-specific training data as illustrated in Figure 2. The purpose is to identify each ECG beat into one of the five classes: N (beats originating in the sinus mode), S (supraventricular ectopic beats), V (ventricular ectopic beats), F (fusion beats), and Q (unclassifiable beats). In this study, ECG records from the benchmark MIT/BIH arrhythmia database [30] were used for both training and performance evaluation. There are a total of 48 records in this benchmark database and each record has two-channel ECG signal for 30-min duration selected from 24-hour recordings of 47 individuals. A total of 83648 beats from all 44 records were used as test patterns for performance evaluation. The proposed method has achieved the highest average accuracies (99% for VEB and 97.6% for SVEB) on arrhythmia detection with the minimal computational complexity.

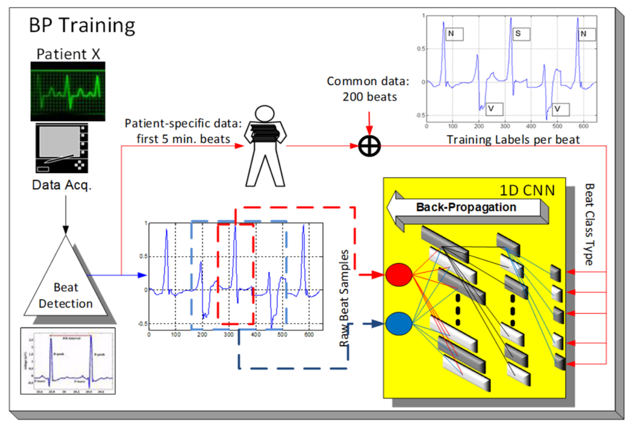

Figure 2: Overview of the proposed approach in BP training [17].

A continuation of this work can be found in [17]. Several studies on arrhythmia detection and identification have been proposed ever since, e.g., [12], [13], [27]-[29]. However, all such studies focused on ECG beat classification for cardiac patients and strictly require a certain duration of training samples (e.g. 5 minutes) containing both normal and abnormal beats of the patient. In the absence of abnormal beats, which is the case of a healthy person, such methods cannot be applied for the early detection of abnormal beats for an otherwise healthy person with no past history of cardiac problems. This is basically a "Chicken and Egg" problem where one needs a certain amount of abnormal samples to learn their characteristics in order to discriminate them from normal beats. A recent study [15] addressed this crucial problem and proposes a "personalized" solution for the early detection of cardiac arrhythmia as the moment they appear on a healthy person. This became the first attempt to propose a personalized early detection of ECG anomalies and cardiac health monitoring. In the absence of real abnormal beats this becomes a far more challenging problem than the patient-specific ECG beat classification. The key accomplishment in this work is that the common causes of cardiac arrhythmias are modelled by a set of filters and then they are used to synthesize appropriate potential abnormal beats of a healthy person as illustrated in Figure 3. Upon learning the healthy person's (real) normal beats and potential (synthesized) abnormal beats, the proposed system with 1D CNNs can then be used to detect any abnormal beat which may occur during monitoring. Without using the real abnormal beats in training, the proposed method has achieved accuracy level, Acc = 80.1% and false-alarm rate, FAR = 0.43%. The average probability of missing the first abnormal beat, therefore, is 0.199 and the average probability of missing all three consecutive abnormal beats is around 0.0079. So detecting one or more abnormal beat(s) among the first three occurrences is highly probable (> 99.2%).

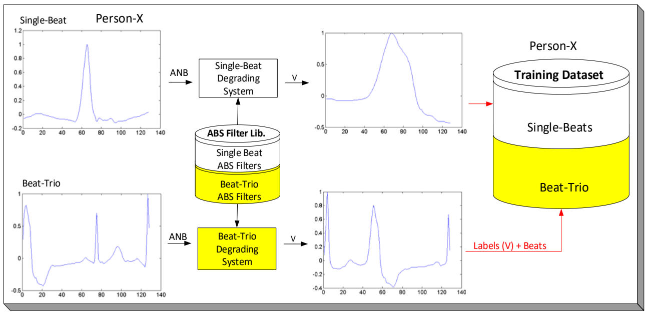

Figure 3: The creation of the training dataset for Person-X using a limited number of real N-beats [15].

B. *Applications with Vibration Signals*

For structural health monitoring (SHM) damage detection based on the vibration signals became the primary focus for civil, mechanical and aerospace engineers over the last decades. Early and meticulous damage detection has always been one of the principal objectives of SHM applications. It is not surprising that the most accurate methods are among the machine learning algorithms. The conventional methods available in the literature involved two processes, feature extraction and feature classification. A paradigm shift has recently occurred with the studies [14], [18], [19], and [20], which have shown that 1D CNNs can achieve state-of-the-art damage detection accuracy in real-time and with the minimal training. It was indeed the first time that compact 1D CNNs have proven to be able to accurately distinguish such complex and uncorrelated signals that can even defy a human expert inspector such as the two samples shown in Figure 4. Using an ordinary computer, when the performance of the proposed approach was tested over the 4.2mx4.2m QU grandstand simulator with 30 joints, all the damage joints were detected without any misses or false alarms, and the detection speed was 45x faster than real-time speed.

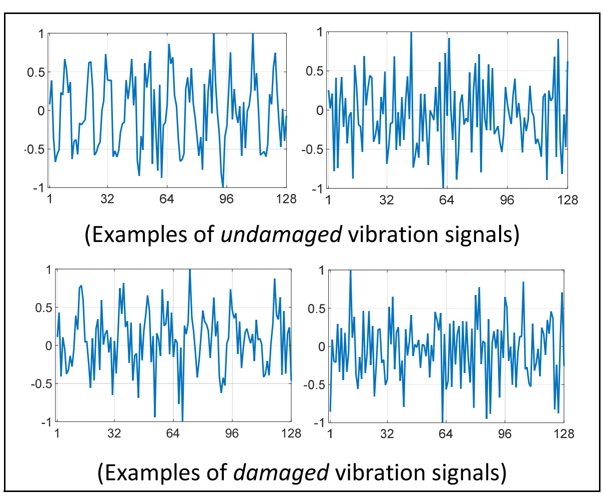

Figure 4: Two pairs of sample vibration signals from normal (undamaged) and damaged structural joints [14].

C. *Applications in Power Machinery and Circuits*

In both applications, it is crucial to detect the anomaly as soon as it appears so as to avoid large-scale damages or even worse, fatal outcomes such as electric discharges or potential explosions. There are numerous studies that are based on machine learning paradigms have been proposed in this domain with varying performance levels. This basically shows how crucial the choice of the right features to characterize the electric (e.g. current or voltage) signals monitored. It is a well-known fact that those fixed and handcrafted set of features cannot optimally characterize any possible electric signal and thus for those cases where their discrimination suffers, the detection performance will deteriorate regardless from the classifier used. This is why they cannot accomplish a generic solution that can be used for any electric waveform or data. Similar to other applications, 1D CNNs have the unique capability to optimize both feature extraction and classification in a single learning body and naturally, the two recent studies [23] and [24] have shown that a real-time monitoring and instantaneous anomaly detection can be accomplished with a state-of-the-art accuracy.

In [23] a potential motor anomaly due to the bearing faults is detected using compact 1D CNNs. Bearing faults are mechanical defects that cause slight variations at certain frequencies in the motor-current waveform. Similar to the vibrations signals, it is almost impossible to detect them visually by manual inspection even with a spectral analysis. 1D CNNs can accomplish this thanks to the layered sub-band decomposition performed in their hidden CNN-layers. Figure 5 shows the ROC curves of the 1D CNN method in [23] against the conventional methods, [31]-[34].

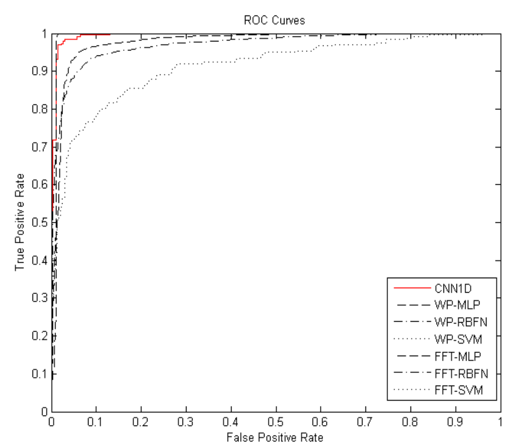

Figure 5: ROC plots of classifiers for comparison. The x- and y-axis represent the false positive rate and true positive rate, respectively [23].

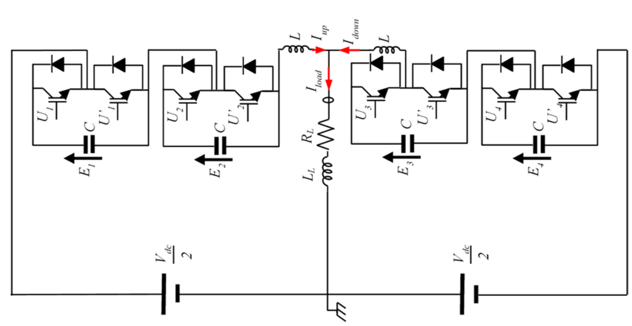

Figure 6: Configuration of the 4-cell MMC circuit [24].

In the modern high-voltage/high power circuitry, modular multilevel converters (MMCs) have been becoming more popular as it can intrinsically provide high power ratings and enable the use of renewable energy sources. A conventional MMC as illustrated in Figure 6 provides a high power-voltage capability with a flexible control of the voltage level. However, reliability and safety became the most crucial challenges for MMCs, which may encapsulate many power switching devices, each of which may be considered as a potential failure site. For instance, an open-circuit fault in a cell will distort the output voltage and current, which will cause an uncontrolled variation of the floating capacitors voltages and leads to the disruption of its operation and even a possible destruction of the MMC.

Although there are numerous studies for anomaly detection in MMC circuits, many of them pose certain drawbacks and limitations which may hinder them in any practical use. For instance some studies proposed to put sensor to each cell which may be neither feasible due to the high cost nor reliable since a sensor may fail too. Some other studies required manual feedback and human interaction. Most of them suffer from high computational complexity that hinders their use in real-time. The frontier study in [24] where the 1D CNN is used first time in the core of the system monitors the cell capacitor voltages and the differential current to detect an open-circuit anomaly almost instantaneously. In brief, the proposed system has accomplished the following objectives [24]:

1. Perfect accuracy on fault detection and identification (e.g. practically 100%),
2. Utmost reliability and robustness against variations of MMC parameters and fault time,
3. Low computational complexity that allows real-time monitoring,
4. Low time delay for fault detection and identification (e.g., <0.1s), and
5. No false alarms.

Besides that this method can easily scale up to very large scale MMCs with hundreds of cells and has the internal capability to detect the multiple faults.

D. Computational Complexity Analysis

Without any exception, in all aforementioned 1D CNN applications a minimal computational complexity is achieved due to two reasons: 1) Compact 1D CNN configuration, 2) No feature extraction or data manipulation (such as 1D to 2D conversion, data augmentation, etc.) are needed. This makes it an ideal tool for a real-time application. Besides this, compact 1D CNNs do not require a special hardware, an ordinary computer or even a low-power mobile device (e.g. a mini-computer or hand-held device with a sensor) will suffice to make the real-time monitoring and analysis possible.

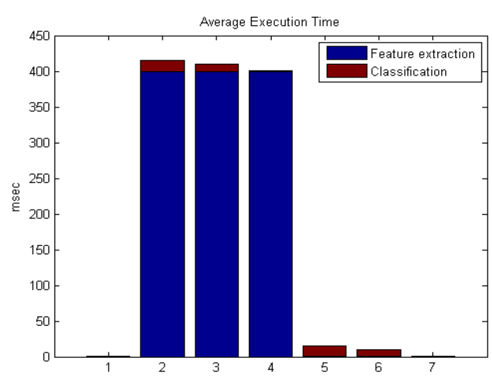

Figure 7: The average execution times (in *msec*) of the proposed algorithm [23] in (1) and six competing algorithms (2-7).

Due to the space limitations, we shall report the average computation times for the proposed and competing methods only on motor fault detection application as given in Figure 7. The competing methods are from [31]-[34].

IV. Conclusions

This paper has revised the major signal processing applications of the compact 1D CNNs. The recent studies have shown that with a proper systematic approach compact 1D CNNs can achieve the state-of-the-art performance with minimal computational complexity. This is especially important for those applications where the labeled data for training is scarce and a low-cost, real-time implementation is aimed.

Appendix

A. Forward and back-propagation in CNN-layers

In the CNN-layers, one-dimensional forward propagation (1D-FP) is defined as:

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} \mathrm{conv1D}\left(w_{ik}^{l-1}, s_i^{l-1}\right) \qquad (1)$$

where x_k^l is defined as the input, b_k^l is defined as the bias of the k^{th} neuron at layer l, s_i^{l-1} is the output of the i^{th} neuron at layer $l-1$, w_{ik}^{l-1} is the kernel from the i^{th} neuron at layer $l-1$ to the k^{th} neuron at layer l. The output y_k^l can be written from the input x_k^l as,

$$y_k^l = f\left(x_k^l\right) \quad \text{and} \quad s_k^l = y_k^l \downarrow ss \qquad (2)$$

where s_k^l stands for the output of the neuron and $\downarrow ss$ represents the down-sampling operation with factor, ss.

The back-propagation (BP) methodology can be summarized as follows. The BP of the error starts from the output MLP-layer. Assume $l = 1$ for the input layer and $l = L$ for the output layer. Let N_L be the number of classes in the database; then, for an input vector p, and its target and output vectors, t_i^p and $\left[y_1^L, \cdots, y_{N_L}^L\right]$, respectively. With that, in the output layer for the input p; the mean-squared error (MSE), E_p, can be expressed as follows:

$$E_p = \mathrm{MSE}\left(t_i^p, \left[y_1^L, \cdots, y_{N_L}^L\right]\right) = \sum_{i=1}^{N_L}\left(y_i^L - t_i^p\right)^2 \qquad (3)$$

To find the derivative of E_p by each network parameter, the delta error, $\Delta_k^l = \frac{\partial E}{\partial x_k^l}$ should be computed. Specifically, for updating the bias of that neuron and all weights of the neurons in the preceding layer, one can use the chain-rule of derivatives as,

$$\frac{\partial E}{\partial w_{ik}^{l-1}} = \Delta_k^l y_i^{l-1} \quad \text{and} \quad \frac{\partial E}{\partial b_k^l} = \Delta_k^l \qquad (4)$$

Then, the BP of the delta-error from the next layer (l+1) to layer l is expressed as:

$$\frac{\partial E}{\partial s_k^l} = \Delta s_k^l = \sum_{i=1}^{N_{l+1}} \frac{\partial E}{\partial x_i^{l+1}} \frac{\partial x_i^{l+1}}{\partial s_k^l} = \sum_{i=1}^{N_{l+1}} \Delta_i^{l+1} w_{ki}^l \qquad (5)$$

Following BP to the input delta, Δ_k^l, as,

$$\Delta_k^l = \frac{\partial E}{\partial y_k^l}\frac{\partial y_k^l}{\partial x_k^l} = \frac{\partial E}{\partial \mathrm{us}_k^l}\frac{\partial \mathrm{us}_k^l}{\partial y_k^l} f'\left(x_k^l\right) = \mathrm{up}\left(\Delta s_k^l\right)\beta\, f'\left(x_k^l\right) \qquad (6)$$

where $\beta = (ss)^{-1}$. Then, the BP of the delta error $\left(\Delta s_k^l \xleftarrow{\Sigma} \Delta_l^{l+1}\right)$ can be expressed as:

$$\Delta s_k^l = \sum_{i=1}^{N_{l+1}} \mathrm{conv\ 1Dz}\left(\Delta_l^{l+1}, \mathrm{rev}\left(w_{ki}^l\right)\right) \qquad (7)$$

where $\mathrm{rev}(.)$ is used to reverse the array and $\mathrm{conv\ 1Dz}(.,.)$ is used to perform full convolution in 1D.

Further details of the BP algorithm are skipped here due to space limitations and can be found in [14] and [23].

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