Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2019) 27: 1752 – 1764
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doi:10.3906/elk-1712-397

A novel algorithm for frequency extraction of ABS signals by using DTDNNs

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Received: 30.12.2017 • **Accepted/Published Online:** 17.12.2019 • **Final Version:** 15.05.2019

Abstract: Intelligent transportations system (ITSs) have emerged to increase safety and convenience of people in vehicles. In an ITS, communication devices in the vehicle or along the streets send the information gathered from the vehicle to information management centers as well as sending processed information to the vehicle. Furthermore, it is necessary to locate the exact location of the vehicle on a digital map in order to navigate the vehicle precisely in control and navigation systems. One of the technologies for this purpose is the antilock brake system (ABS), which can avoid accidents effectively and can also be utilized to determine vehicle speed and location by using its pulses. To do so, the frequency of ABS pulses should be extracted. In this paper, a novel method for frequency extraction is introduced in which one type of neural network, the distributed time-delay neural network (DTDNN), is used. Simulation results show that the output of the neural network can acceptably follow frequency variations of ABS signals after convergence.

Key words: ABS signal processing, pulse frequency, neural network, intelligent transportations system, ABS sensor

1. Introduction

Traffic is one of the most important challenges in civil transportation systems. Wasting time and natural fuel resources, increasing deaths in accidents, and increasing pollution are major issues that are affected directly by traffic congestion [1]. Intelligent transportations systems (ITSs) aim to provide better transportation systems by using advanced electrical and communication technologies. Such a system may consist of a set of sensors for positioning and direction tracking as well as hardware/software for computation and communication, which aims at effective navigation of humans, vehicles, or any other type of mobile device from one point to another point [2–4]. Nowadays, the ITS is a necessary issue in modern information and communication societies [4].

Using an odometer sensor in a vehicle is one method for extracting speed and the traveled distance of the vehicle. This method is not precise and has significant errors because it is prone to noise. Another method for determining distance, speed, and even direction in modern vehicles is using the precise sensor in antilock brake system (ABS) sensors. These sensors include an optical encoder that generates digital pulses [5]. Figure 1 illustrates the scheme of this sensor.

An example of decoder output pulses is shown in Figure 2. The number of vehicle wheels' rotations can be computed by sampling these pulses. Velocity and traveled distance may be achieved by subsequently using dynamic equations. Another advantage of this approach is obtaining the direction of vehicle movement, as well as high accuracy, so that when the vehicle rotates to the right or left, speeds of the front and rear wheels are

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Figure 1. Illustration of an optical encoder available in an ABS sensor.

different. Thus, by calculating wheel speeds in terms of each other and by using vehicle dynamic equations, one can determine the vehicle's direction [5].

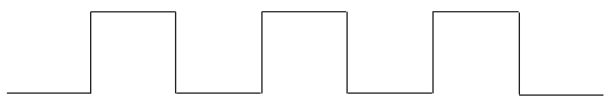

Figure 2. An example of ABS decoder output pulses.

It should be noted that this approach has cumulative errors like other approaches. In practice, to achieve an accurate positioning system, one can combine the information of vehicle internal sensors with an external positioning system such as GPS [2,5–10].

The motion vector for the vehicle in every instance of time can be defined by using the velocity and direction of the vehicle. In order to determine the linear speed of the vehicle, the angular speed of the front wheels should be defined. The relationship between angular speed and linear speed of the wheels is given by [11]:

$$|V| = \omega_i \times R, \tag{1}$$

where R is the radius of the wheel.

A kinematic model of the vehicle is shown in Figure 3 on the X-Y coordinate system, where the rear wheels are always parallel to the car body and allowed to roll or spin with no slip. The front wheels can turn to the left or right, but they are parallel together. Since ABS measurements provide the attitude of the rear wheels, the rear wheels' kinematic model of the vehicle can be considered for simulation purposes. The discrete kinematic equations of the mobile vehicle with respect to the axle center of the rear wheels can be expressed as:

$$v_k = \frac{1}{2}\left(V_k^R + V_k^L\right), \tag{2}$$

$$\theta_k = tan^{-1}\left(\frac{d}{V_k^R - V_k^L}\right), \tag{3}$$

where V_k^R, V_k^L, and v_k are the linear velocity of the rear right/left wheel and average velocity of the rear wheels, respectively. Furthermore, θ_k is the instantaneous angle of the center of rotation, d is the distance between the vehicle's rear wheels, and Δt is the sampling time.

As is evident from the equations, V_k^R and V_k^L are essential variables for the ABS navigation system.

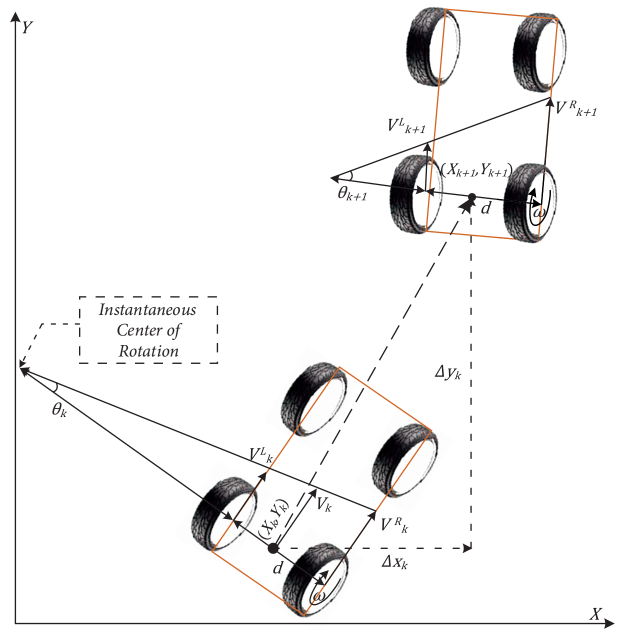

Figure 3. Illustrative representation of the key parameters in the vehicle kinematics.

With the assumption of rigid vehicle wheels, they can be calculated as follows:

$$V_k^R = r\omega_k^R$$

$$\omega_k^R = \frac{2\pi}{nT_k^R} \tag{4}$$

$$V_k^L = r\omega_k^L$$

$$\omega_k^L = \frac{2\pi}{nT_k^L} \tag{5}$$

where ω_k^R and ω_k^L are the angular velocity of the rear right and left vehicle wheels, respectively; T_k^R and T_k^L are respectively the ABS signal periods of the rear wheels; n is the number of pulses generated per wheel revolution; and r denotes the radius of the vehicle's wheel.

The frequency extracted by our method can be used for defining traveled distance as well as heading of the vehicle in a known time interval, which can be utilized for navigation. In this paper, we represent a scheme for frequency extraction of ABS signals, by which navigation for vehicles can be achieved. This system may be added to a GPS system so that in situations in which the GPS signal is weak and navigation via GPS faces high error rates, such as with low velocity of the vehicle, on dense streets with tall buildings, and in road turns, we can use navigation with ABS signals temporarily. This fusion of ABS and GPS systems will be investigated in another research work by our research group.

To implement such a system, first proper hardware for extracting and sampling should be provided by understanding ABS signal characteristics. Then frequency contents and angular speeds of the wheels should be calculated by utilizing signal processing methods [12].

In this paper, we introduce a novel method for extracting the ABS signal frequency by using a special kind of neural network. The remainder of this paper is organized as follows. In Section 2, ABS signal characteristics are discussed. Processing of ABS signals by neural networks as well as an introduction to the utilized neural network are investigated in Section 3. In Section 4 hardware system specifications and implementation are discussed. Simulation results are concluded in Section 5. Finally, a conclusion is offered in Section 6.

2. ABS signal characteristics

As mentioned before, an ABS signal is a series of subsequent pulses with deterministic and fixed amplitudes, where the frequency determines the number of the wheel's rotations in a time unit, which is called angular speed. Extraction of the frequency of ABS pulses in ideal conditions (without noise) is not a difficult task. However, different issues lead to noisy versions of signals and even cause signal destruction. Some of these factors are as follows [6,8,10]:

- Thermal noise in the vehicle's engine,
- High vibration in vehicles' wheels during movement and direct effects on ABS mechanical sensors,
- Common power supply in the vehicle and the effect of electrical current consumed by other parts of the vehicle [13],
- Environmental conditions such as high humidity or hot weather.

As a result, these issues lead to ABS signals with high levels of noise. Figure 4 illustrates an ABS signal sample, which is sampled at a frequency of 4800 samples/s, and its spectrum. These figures result from practical data. Figure 4a illustrates the ABS signal and its spectrum at speeds of 10 and 20 kph. When the vehicle moves at very low speed, the ABS signal and its spectrum are as shown in Figure 4b. By pushing the brake, the ABS signal and its spectrum have patterns like in Figure 4c, and when the machine has no movement these signals have patterns like in Figure 4d.

Furthermore, an autocorrelation function for ABS signals is shown in Figure 5. As can be seen from the figure, the ABS signal has a high level of noise and this causes complexity in calculating the pulse frequency.

3. ABS signal processing with neural network

There are various approaches to extracting the fundamental component of frequency from a noisy ABS signal [6,10,11,14,15]. Since the positioning system is real-time, signal processing methods must have the following capabilities [12]:

- It should allow the tracking of variations of the pulse's instantaneous frequency.
- It should converge to the fundamental frequency with a low number of samples (in short intervals of time).
- It should cover the variation range in the frequency of the ABS signal (between 0 to 1000 Hz in accordance with the vehicle's speed).
- It should have the ability to reduce noise in the pulse.
- It should allow implementation in hardware modules such as microcontrollers or FPGAs.

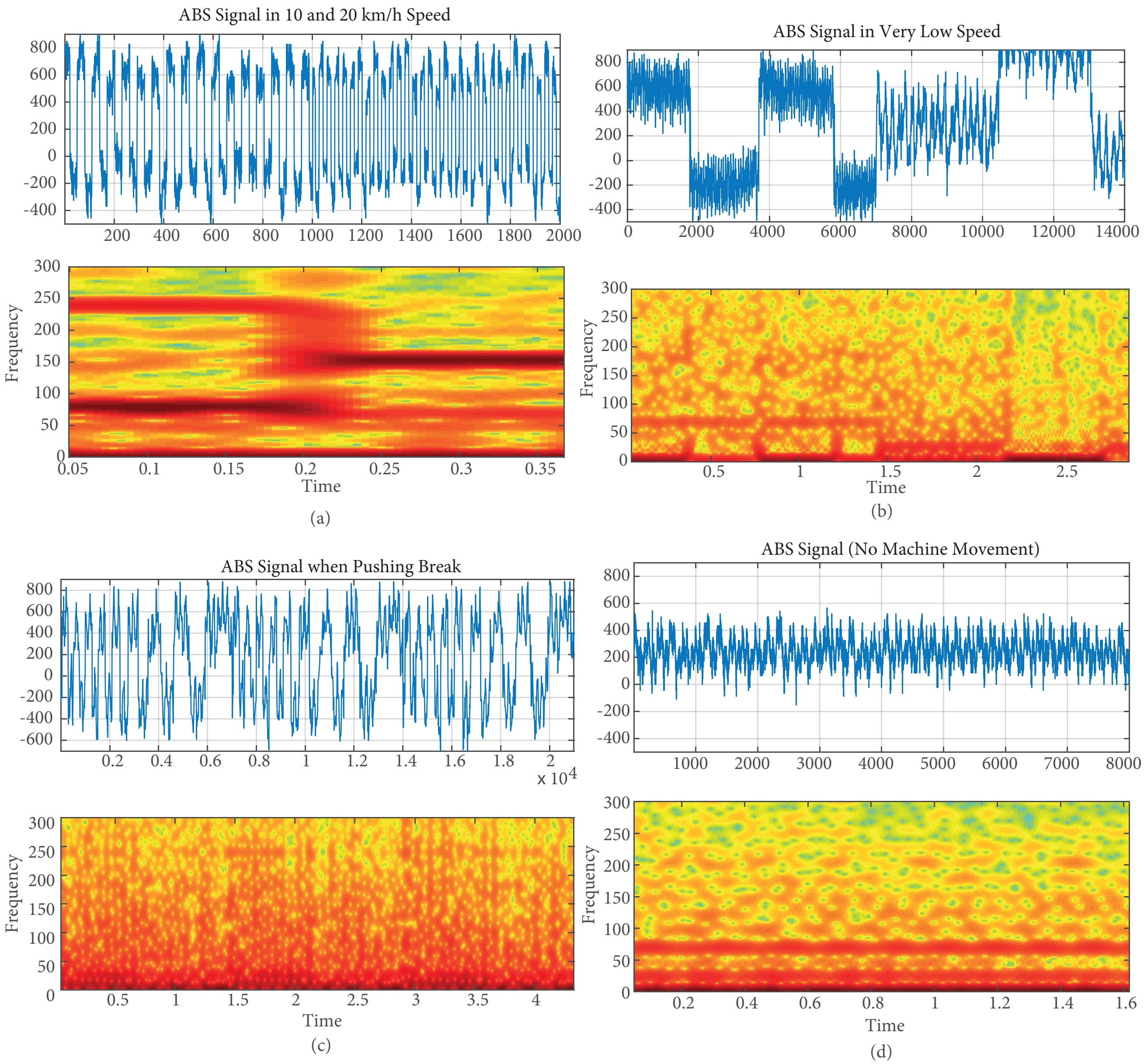

Figure 4. Some types of ABS signals in different conditions of the vehicle: (a) speeds of 10 and 20 kph, (b) very low speed, (c) pushing brake, (d) no machine movement.

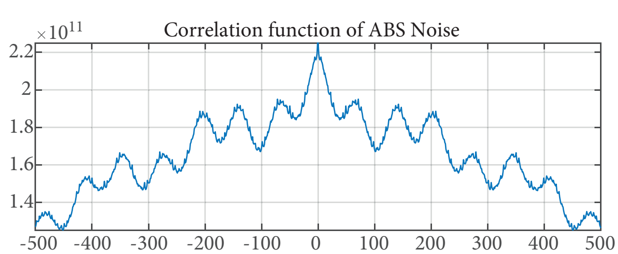

Figure 5. Correlation function of ABS signal.

A signal processing method based on a neural network is proposed in this paper according to the above specifications. If these kinds of networks are selected and trained properly, they allow frequency components of noisy ABS signals to be extracted properly and variations to be tracked. Furthermore, the implementation is straightforward based on the availability of programmable hardware modules specific for these networks [16].

Neural networks can be categorized in static and dynamic categories. In static networks the output of the network is obtained directly from network inputs at the same time, and they also have no feedback or delay elements. Training of these networks is known as the backpropagation method. In dynamic networks the outputs not only depend on network inputs in the current time, but also depend on previous values of outputs and inputs [17].

In this paper, we have used a dynamic type of neural network known as a distributed time-delay neural network (DTDNN), which is shown in Figure 6 in the special case of a two-layer neural network. A DTDNN provides a simple and efficient way of classifying datasets due to high speeds and fast conversion rates as compared with other learning techniques. A DTDNN is a dynamic network that is generally more powerful than static networks because dynamic networks have memory; they can be trained to learn sequential or time-varying patterns. This has applications in such disparate areas as prediction in financial markets, channel equalization in communication systems, phase detection in power systems, sorting, fault detection, speech recognition, and even the prediction of protein structures in genetics [17]. However, static (feedforward) networks have no feedback elements and contain no delays; the output is calculated directly from the input through feedforward connections. The training of static networks was discussed in backpropagation. In dynamic networks, the output depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network. A delay chain of an arbitrary length can be inserted in the input of each layer in the network as shown in Figure 6. The DTDNN was first introduced to recognize tone in speech signals [6,14,16]. However, more studies revealed that it can be utilized in similar cases for nonspeech signals. According to what was mentioned above and also based on the scope of ABS signal processing, which is extraction of the fundamental harmonic in the signal, we focus on utilizing this kind of neural network in extracting the fundamental frequency component of the ABS signal.

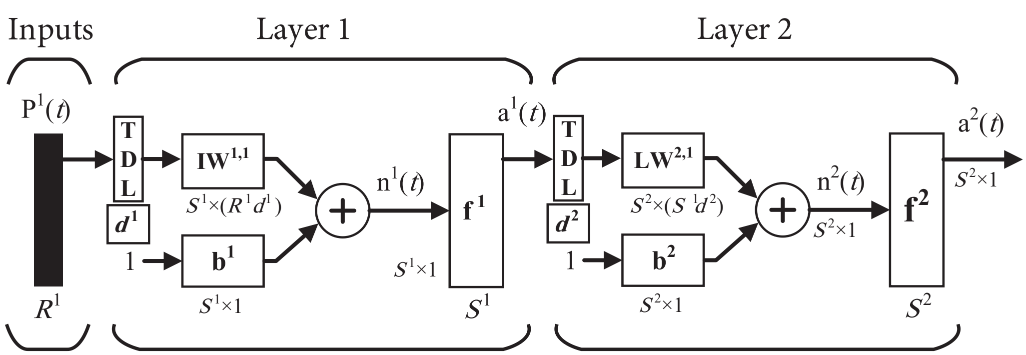

Figure 6. Two-layer structure of DTDNN [17].

3.1. Design of DTDNN

The DTDNN, like other neural networks, operates with multiple interconnected layers of perceptrons and is implemented as a feedforward neural network. All neurons (at each layer) of a DTDNN receive inputs from the outputs of neurons in the layer below. Unlike regular multilayer perceptrons, all units in a DTDNN, at each layer, obtain inputs from a contextual window of outputs from the layer below. For time-varying signals each unit has connections to the output from units below but also to the time-delayed (past) outputs from these same units [17].

According to sampled data for vehicle speeds from 0 to 100 kph, the range of ABS signal frequency will be 0 to 900 MHz. Hence, we have chosen training data for the network as a set of pulses with frequencies of 3 to 900 MHz with resolution of 5 Hz. Since mechanical operations are real-time, the time duration of data has been considered as 0.1 s. To design the network, two layers and delay chains with lengths of 50 and 40 are considered in the first and second layers, respectively. The number of cells in the first and second layers has been assumed to be 9 and 1, respectively. In other words, the number of cells in the first layer is $\mathrm{S}^1 = 9$, so the number of variables in the first layer will be $(50 \times 9) + 9 = 459$ in which 9 biases are added to 450 variables. Consequently, there is one cell in the second layer, so $\mathrm{S}^2 = 1$, and thus the number of variables in the second layer will be $(40 \times 1) + 1 = 41$, in which one bias is added to 40 variables. As research shows, the performance of the network will be improved by increasing the number of cells in the first layer. However, this may increase the number of parameters in the optimization process, which may cause the training time of the network to be increased significantly. The transfer function of the first layer is tansigmoid and for the second layer it is purelin, which are called f^1 and f^2, respectively.

In theory, this delay chain is chosen so that one cycle of the signal is covered, although this can be accomplished by choosing the length of the delay chain to be less than the length of one cycle of signal, which is an experimental issue. To do so, we recorded the output of the sampler for vehicle speeds from 0 to 100 kph. It was used as a priori information. Then we calculated a frequency range of 0 to 200 Hz according to this velocity log according to Eq. (1). Assuming that minimum frequency is $f_{min} = 3\,\mathrm{Hz}$, $T_{max} = 0.33\,\mathrm{s}$ to cover one cycle of the ABS signal; thus, by considering sampling frequency as 3000 samples per second, the total number of samples in one cycle is $T_{max} \times 3000 = 1000\,\mathrm{samples}$. Furthermore, if maximum frequency is $f_{max} = 200\,\mathrm{Hz}$, then $T_{min} = 0.005\,\mathrm{s}$ to cover one cycle of the ABS signal; thus, by considering sampling frequency as 3000 samples per second, the total number of samples in one cycle is $T_{min} \times 3000 = 15\,\mathrm{samples}$.

Based on sampling frequency, the large number of samples in one cycle of the ABS signal results in more complexity and high processing time. Thus, a trial and error method is used to determine the chain lengths of the layer to achieve a more appropriate smaller length for the length of the delay chain. In other words, the same results may be achieved by using 80% of chain lengths for the layer. Thus, there is a trade-off between length of the chain and complexity of the system as well as being real-time. As the length of the delay chain increases, rapid changes of the ABS signal cannot be tracked well. If the length of the delay chain is short, not enough data will be present for frequency extraction.

3.2. Training and target data of the DTDNN

Coefficient matrices ($\mathrm{IW}^{1,1}$, $\mathrm{IW}^{2,1}$) and bias vectors (b^1, b^2) must be weighted, such that the output of the neural network should result in the frequency of the input signal. Figure 7 illustrates a portion of the network input pulse (training data) as well as the target output signal. Input training data of the network are shown in Figure 7a and target values in the network output are illustrated in Figure 7b. A spectrogram of training data and target values is represented in Figure 7c.

Since the ABS signal has noise added to it, it is better to train the network with noisy training data initially. Such training data are achieved by adding random noise with zero mean and variance 0.1 to the noiseless training data. This signal is shown in Figure 8.

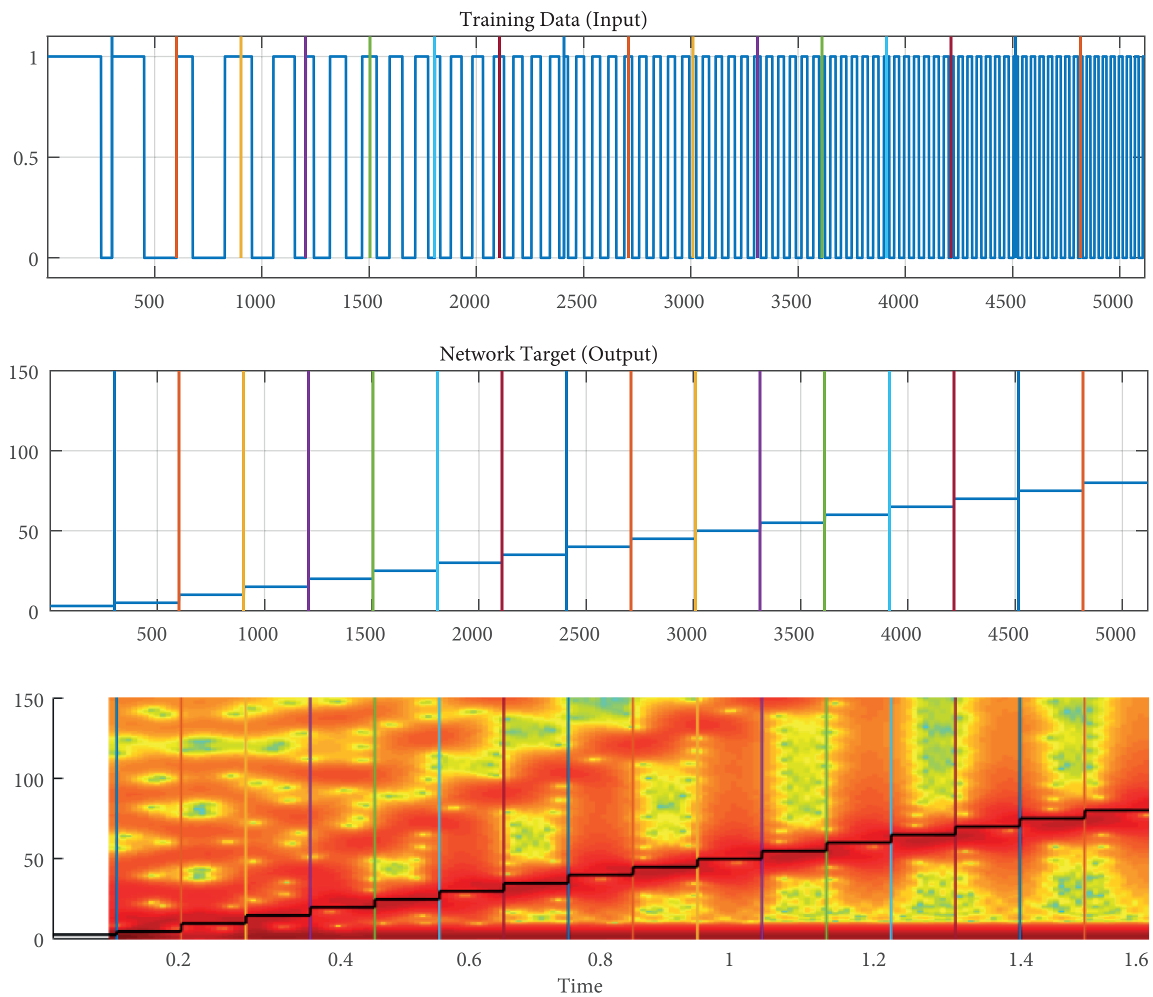

Figure 7. (a) Input training data of the network (from 3 to 80 Hz), (b) target values in the network output, and (c) spectrogram of training data and target values. Time duration of each pulse is 0.1 s.

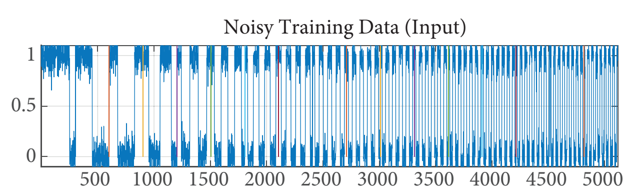

Figure 8. Noisy training data (from 3 to 80 Hz).

3.3. Neural network training scheme

As mentioned in the previous section, coefficient matrices and bias vectors must be weighted, such that the output of the neural network should result in the frequency of the input pulse. To do so, we have used a training method called trainbr. This method is a network training function that updates weights and bias values based on the Levenberg–Marquardt optimization algorithm. The goal of this algorithm is to minimize the linear combination of the square error of input/output and weights. This process is called Bayesian regularization [17,18]. Furthermore, this method modifies this linear combination so that the network achieves acceptable performance at the end of the training process. The Bayesian regularization process is implemented by the Levenberg–Marquardt algorithm [18]. To calculate the Jacobean matrix of the cost function in terms of parameters such as weights (W) and biases (b) in this algorithm, the backpropagation method is utilized. Note that the target value of error for neural networks is assumed to be 10^{-5} and the number of training samples is considered as 8000 samples, which are sampled at a sampling frequency of 3000 samples per second.

4. Hardware system specifications and implementation

In this paper, many experiments have been done for evaluating the performance of the ABS system and surveillance algorithms. In these implementations, ABS sensors of a Peugeot 206 have been utilized [19], as shown in Figure 9.

Figure 9. The vehicle under test and its hardware.

Figure 10 illustrates a detailed block diagram of the system. As shown in Figure 10, first the output signal of the ABS sensors passed through a low-pass filter in order to decrease noise. Then the filtered ABS signals were amplified to a proper level and consequently forwarded to AVR-ATmega32 microcontrollers for sampling and data aggregation. The microcontroller calculates the instantaneous velocity of the vehicle by applying 512-point fast Fourier transform (FFT) to the sample data and determining its frequency. Finally, data packets were transmitted to a central computer via a serial port. In this paper, we have used MATLAB software for processing.

5. Simulation results

As mentioned in previous sections, in order to train the network, a set of noisy pulses is considered, which are added by Gaussian noise with variance of 0.1. The frequency of these pulses is 3 to 410 Hz with frequency resolution of 5 Hz. The sampling frequency of the training signal is 3000 samples per second, which corresponds to the sampling frequency of ABS signals. Some parameters of the neural network are shown in Figure 11. The sum of square errors is illustrated in Figure 11a and Figure 11b shows the sum of square weights. Furthermore, the number of effective parameters after 10 training iterations is illustrated in Figure 11c. According to these figures, as training iterations of the system increase, the sum of square errors decrease; however, the effective parameters of the network increase. After 10 training iterations, it can be concluded that the network converges

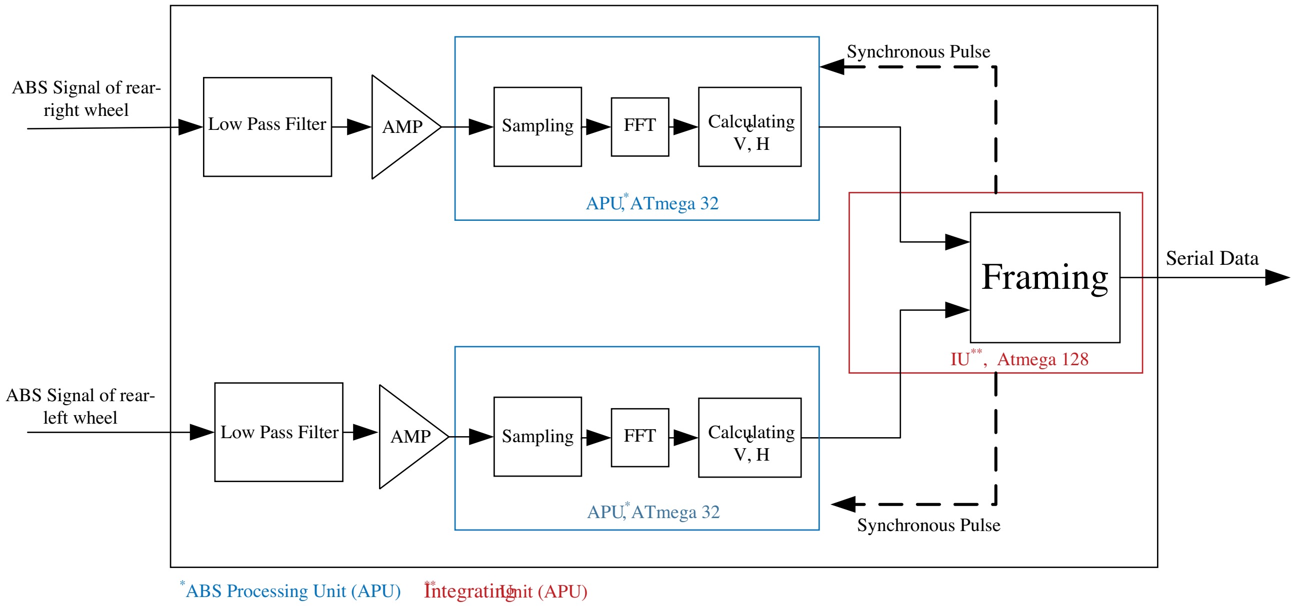

Figure 10. The hardware block diagram.

to its final value, relatively and by increasing the training iterations, no significant variations happen in the performance curves.

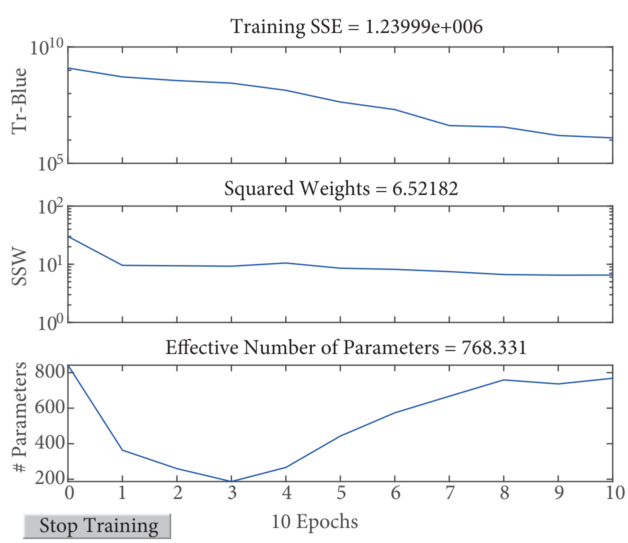

Figure 11. (a) Sum square error, (b) sum of square weights, and (c) number of effective parameters after 10 training iterations.

In order to decrease network output variations and achieve much smoother output, a rectangular AR filter with length of 300 is used at the output of the network. Figure 12 represents training data and network output. Figure 12a illustrates noisy training data, and neural network output after convergence is shown in Figure 12b. Moreover, Figure 12c represents the spectrogram of the noisy training data and network output. According to this figure, the output of the network can acceptably follow frequency variations of training data until the end of the pulse duration time. The number of samples in each training pulse is 3000, which means the network should be able to converge to its defined target value (pulse frequency) after s samples of input data. By assuming sampling frequency of 3000 samples/s, this number of training samples will prolong 0.1 s.

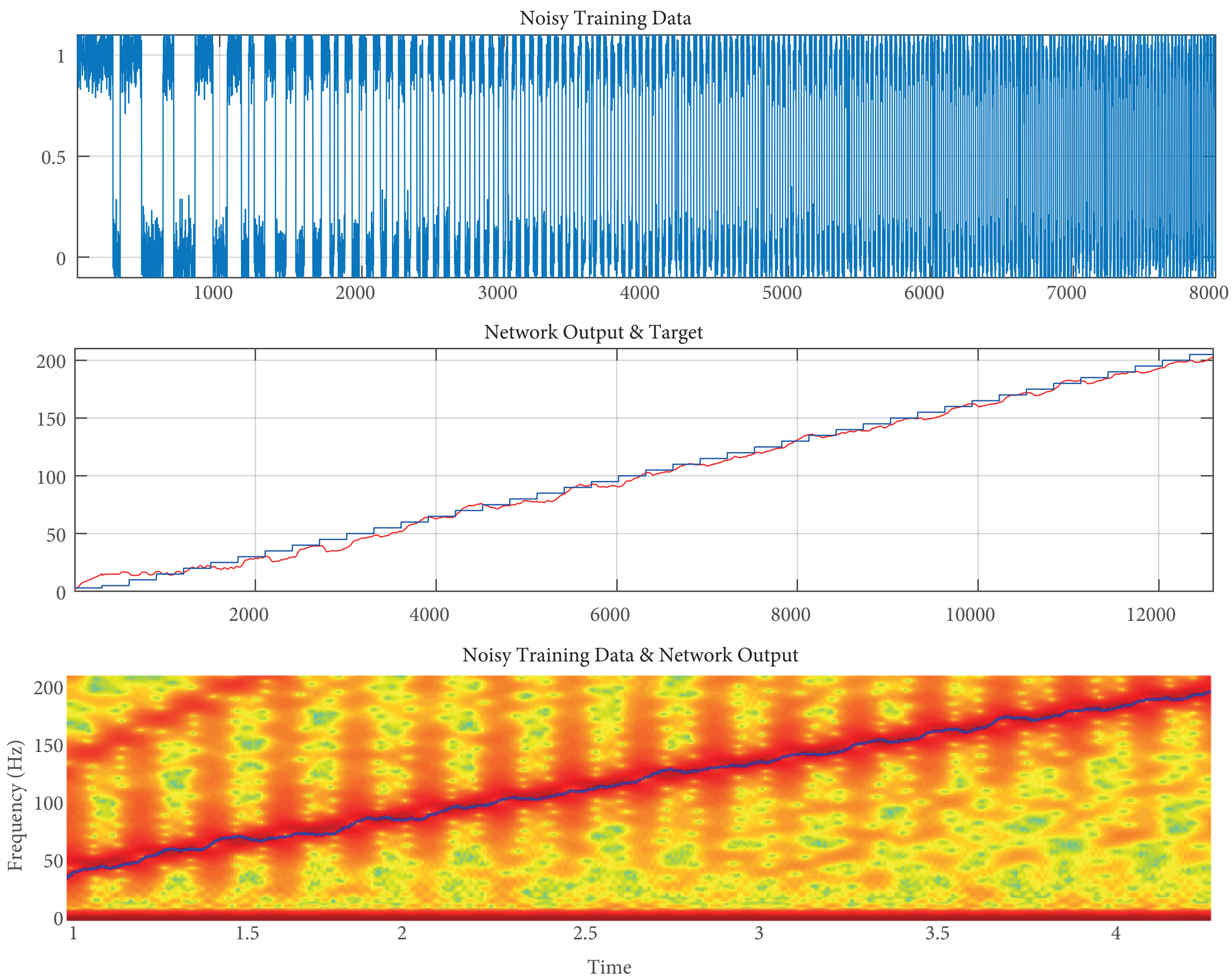

Figure 12. (a) Noisy training data, (b) neural network output after convergence, and (c) spectrogram of noisy training data and network output.

The ABS signal is sampled at a rate of 3000 samples/s after it passes its corresponding hardware, and then it enters the trained neural network to extract its frequency contents. Figure 13 shows the ABS signal (Figure 13a), neural network output after convergence (Figure 13b), and the spectrogram of ABS signals and network output (Figure 13c). According to this figure, the output of the network can follow frequency variations of the ABS signal acceptably.

6. Conclusion

A novel approach for extracting the frequency of ABS signals by using DTDNNs has been proposed in this paper. Coefficient matrices and bias vectors are trained and weighted such that the network output converges to frequency for the input pulse. Simulation results show that the sum of square error decreases by increasing

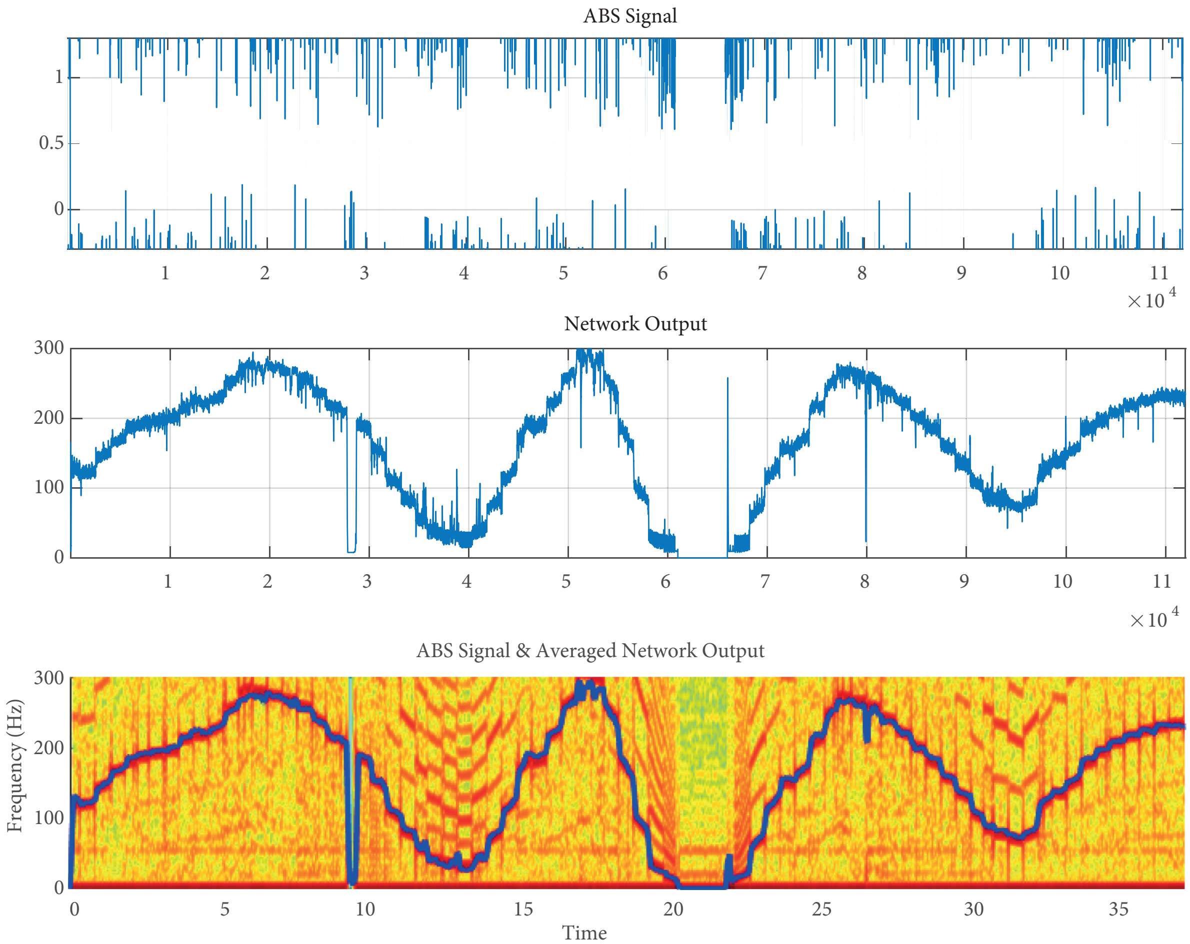

Figure 13. (a) ABS signal, (b) neural network output after convergence, and (c) spectrogram of ABS signal and network output.

network training iterations; however, the number of effective parameters increases. After 10 iterations, the network relatively seemed to converge to its final value and no significant variations were observed in performance curves by increasing training iterations. The neural network output after convergence and the ABS signal spectrogram show that the network output follows the variations of ABS signal frequency acceptably.

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