A Comparison of Real-Time Extraction between Chebyshev and Butterworth Method for SSVEP Brain Signals

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***Abstract*—In this paper, a comparison of real-time extraction using the IIR Chebyshev of 4 order and the IIR Butterworth of 6 order methods is proposed. In the Experiment, the steady-state visual evoked potential with stimuli frequencies of 7,5 10, 15, and 20 Hz is used to control the wheelchair directions (i.e., stop, forward, right, and left). The data were collected from a session in which fourteen subjects with age about 24±2 years were tested. The total average classification accuracy of 82% and 62.2% for Chebychev and Butterworth extraction method are achieved. The higher average classification accuracy of 100% and 92.8% for both methods, respectively, are obtained for forward direction (8.75-12.5Hz).**

***Index Terms*—Butterworth; Chebyshev; EEG-SSVEP; Feedforward Neural Networks.**

I. Introduction

The brain consists of billions of nerve cells called neurons that are interconnected each other to form a network (electrical current occurs in nerve cells) [1]. The flow of electricity in the brain is essentially caused by the movement of negative and positive ions out of the cell and cross from one fiber to another. The brain regulates and coordinates thoroughly of the body such as movements, behaviors, and their functions such as muscle movement, organ activity, and the center for human awareness of stimuli (hot, cold, touch, visual, hearing, etc). Therefore, if we can exactly identify and differentiate the pattern of brain signals related to the given stimuli such as movement, behaviours, and their functions, not only the body but the environment also can be controlled.

Electroencephalogram (EEG) is a noninvasive measurement method to capture the electrical activities of the brain on the scalp over multiple areas. The measurement of currents that flow during synaptic excitations from a neuron to another in the cerebral cortex area is called EEG signal. The EEG signals, which is important in clinical application (i.e., for diagnosing, monitoring, and managing neurological disorders) and in research field (i.e., brain-computer interface (BCI) application), is extensively contaminated by a variety of large signal or noise [2].The EEG signals consist of many data points, however it can only be compressed into a few parameters as a feature to differentiate desired information. The represented feature of the EEG signals is particularly important for recognition, identification, and others external application purposes. Detecting and analyzing biosignals of the human brain is very important to figure out the brain construction, operational function, and how those information could be applied to environment control. The application of brain signals detection has been developed in various fields. From many available biosignals, steady-state visual evoked potential (SSVEP) is one of the important biosignals of the brain which has a wide application in examining brain activity and cognitive functions [2]. These signals are natural responses for visual stimulations at specific frequency range. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, normally the brain will generate an electrical activity at the same (or multiples of the) frequency of the designed visual stimulus. This method is used by the brain to differentiate which stimulus the subject is looking at in case of stimuli is flashed with different frequency [3, 4].

Numerous applications of the EEG based SSVEP are as a communication tool by people with neuromuscular disorders (such as BCI wheel-chair) [2, 5-17], as audio speller [18], and a lie detector [19]. Recently, a great variety of its potential applications have been widely studied such as smart homes, internet browsing, market researchers, and BCI for controlling hand grasp [20]. Previous research has shown that several aspects of the ERP (especially the latency and magnitude) are highly variable across trials. Many procedures appeared in research area to resolve the problem of EEG (specifically for obtaining maximum amplitude of SSVEP) are not sufficiently standardized yet.

In this paper, a real-time extraction method between IIR Chebyshev of 4 order and IIR Butterworth of 6 order is compared. The designed filter as an extraction method is developed based on the four stimuli frequencies (i.e., f:7.5 (bottom), 10 (up), 15 (right), and 20 (left) Hz) as indicated in visual or intension stimuli in Figure 1. The four peak (i.e., ω: 0.03π, 0.04π, 0.06π, and 0.08π) corresponds to the four stimuli frequencies, respectively. They are converted with $f = fs\,\omega/2\pi$, f is stimuli frequency, fs is the sampling frequency (500 Hz), and ω is the normalized frequency. Through the designed method, it is expected that the appeared maximum power spectrum of the extracted signals are close as possible with the stimuli frequency range by mean the quality of the extracted signals are significantly improved. At last, the extracted signals are classified using an adaptive feed forward neural networks (AFNN) technique. A modular classification AFNN algorithm based on Levenberg-Marquardtin updating parameters is used. The experimental results in this paper show that the implementation of the proposed method achieves a very significant statistical improvement in extracting and classifying the peak of amplitude which helps improve different BCI applications in order to help the people and provide them with efficient solutions. Figure 1 is a proposed scheme of real-time extraction of brain signals for wheelchair movement with designed visual stimuli.

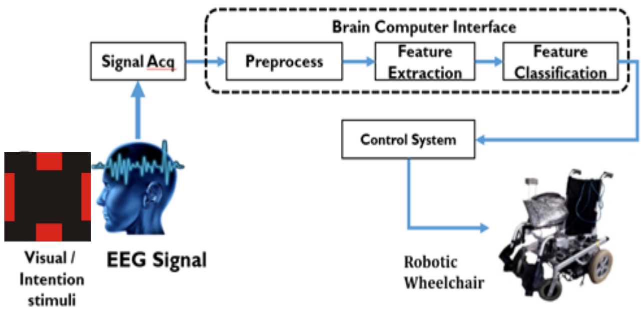

Figure 1: Scheme of real-time extraction of brain signals for Wheelchair-BCI with visual stimuli design: 7.5 (bottom), 10 (up), 15 (right), and 20 (left) Hz indicate the wheelchair go stop, forward, right, and left, respectively

II. METHODS

A. Data Acquisition

In the experiment, fourteen subjects between the ages of 22 and 26 years old (all males, none of whom had any known neurological deficits) were tested. The stimuli were four red square (each measuring 4.1 x 4.1 cm) presented with four different frequencies at the computer screen monitor (see Figure1). The subjects were sited at a distance of 70 cm and focused on one of the flashed red squares according to the intended direction. In brain based EEG recording signals, researchers have normally minimized recorded noise by reducing the impedance between the recording electrodes and the living skin tissue. High electrode impedances do not meaningfully reduce the size of the EEG signal, but they might increase the noise level, resulting in a lower signal-to-noise ratio. In this experiment, less than 5 kΩ impedances is used as shown in Figure 3. The EEG signals are recorded continuously using three electrodes (channels) at O1, O2, and Oz by following the 10-20 International System and digitized at a 500 Hz sampling rate. Each subject records four sessions to indicate four different directions. Different data analysis of this experiment has been published in the other works [21, 22]. For the performance evaluation of the proposed method, two of experiments were conducted.

B. Signal Processing

Preparatory to an analysis of the features of maximum amplitude from recorded EEG-SSVEP signals in real time, actual signals were recorded in three-channel (O1, O2, and Oz) configuration. In the experiment, 19 channels were recorded but in this paper, the data were only processed from the three channels according to the visual stimuli. Two feature extraction methods which are IIR Chebyshev of 4 order and the IIR Butterworth of 6 order are compared in real time. Both proposed design extraction methods are shown in Figure 2 and 3. The cut-off frequencies of band-pass and stop-band filter are designed in the range of 7.25 - 20.5 Hz with an attenuation of -10 dB for Chebyshev and in the range of 3-40 Hz with an attenuation of -25 dB for out of stopband range. In the designed filter of the Butterworth extraction for passband in the range of 6 – 21 Hz according to the given stimulus, the stopband filter must be in the range of 3 – 40 Hz. However, in the Chebyshev extraction, the stopband can be closely assigned into given stimuli which the noise out of the intended frequency ranges is highly removed.

The filtered signal is captured based on the time of the given stimuli. Since the sampling frequency of the EEG system (Mitsar 202) is 500 Hz while the time for each given stimulus is about 5 seconds, then the obtained data is 500 x 5 = 2500 data per 5 seconds. Therefore, for the recording time of 90 seconds, the total obtained data is about 4500 data (i.e., 90 x 500). The filtered EEG-SSVEP signals are then transformed into frequency domain using fast Fourier transform (FFT) algorithm.

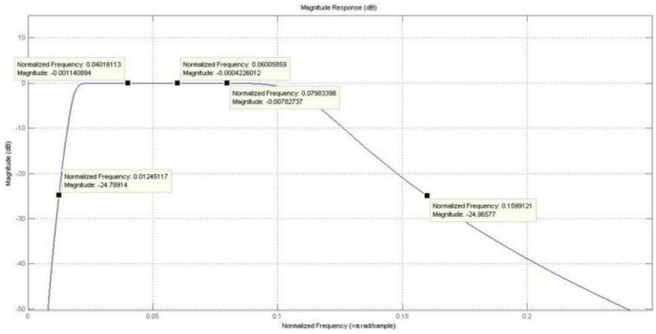

Figure 2: Magnitude Response of the IIR Butterworth of 6 order in the normalized Frequency ω (πrad) scheme of real-time extraction of brain

The feedforward neural network (FNN) is one of the most widely used ANNs [9, 23, 24]. By adaptively updating the varies parameter of the weight in such of classification purpose then the FNN called as adaptive feedforward neural network (AFNN). The neurons in an AFNN are organized as a layered structure and connected in a strict feedforward manner. The network is trained using many different training patterns or features. The information in the network is stored as connection weights, which are updated during the training procedure so as to minimize the total error between the actual outputs generated by the network and the desired outputs which is called supervised learning. The structure of a basic FNN is presented in Figure 4.

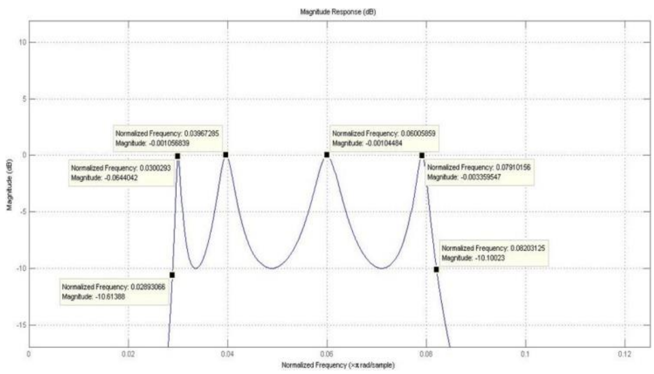

Figure 3: Magnitude Response of the IIR Chebyshev of 4 order in the normalized Frequency ω (πrad)

In the input layer (i.e., the maximum amplitudes from each channel O1, O2, and Oz) and each hidden layer, there is always a bias neuron along with original input neurons and specified hidden neurons. The bias neuron is represented by the symbol '*b*' (1 is used as the input value to bias neurons) in Fig.4. x_n represents the input variable to a neuron. Given the need to train the FNN, bias neurons serve to increase the degrees of freedom of the network and to update the training weights. The use of a bias term is a way of improving training weights at its layer and helps convergence of the weights to an acceptable solution. From Figure 4, the output of the neuron can be written as

$$y = f(\sum_{j=1}^{72} w_j g(z_j) + b_2) \tag{1}$$

$$= f(\sum_{j=1}^{72} w_j g(\sum_{i-1}^{3} v_{ij} x_i + b_{ij}) + b_2)$$

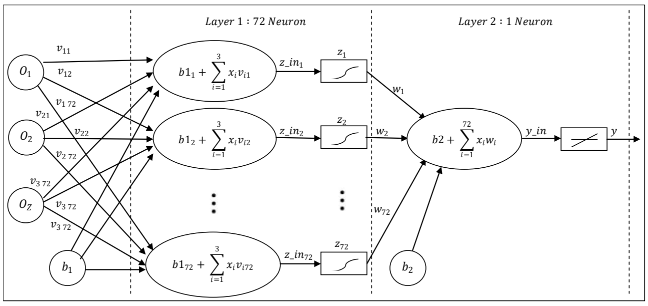

Figure 4: AFNN architecture

where i denote the number of input, j denotes the number of neurons, b indicate the bias of each layer, z indicates the output of networks, x_i are the O1, O2, and Oz as neuron input, v_{ij} are the interconnection weights of the second layer, w_j are the interconnection weights of the second layer, $g(\cdot)$ and $f(\cdot)$ are the activation function of the first and the second layer, respectively, and y is the output of the neuron. In this classification, the output y is obtained in the form of frequency range such as less than 7.5Hz, 7.51-12.5Hz, 12.51-17.5Hz, and more than 17.5Hz.

III. Experimental Results

The raw data, filtered signals using Chebyshev and Butterworth of subject 4 are given in Figures 5- 7. The raw data and filtered signals are almost similar for all subject by mean they are still difficult to differentiate each other since they still corrupted by some artifact. However, it can be roughly seen that the average extracted amplitude using the Chebyshev method is smaller than using the Butterworth method. It is assumed that the result by Butterworth is higher corrupted by artifact but it could be richer with the desired information. In the filter design, the stopband range of the Butterworth is wider than the Chebyshev method. While in the Chebychev design filter, the ripple in the band-pass area is used to pass the frequency of 7.5, 10, 15 and 20 Hz (stimuli frequency) and remove the frequency signal outside the stimuli. However, to avoid the uneven attenuation due to the transition from the pass-band to the stop-band area, the bandwidth is slightly expanded. Those frequencies have designed to be the peak of the Chebyshev filtered by mean the amplitude around those peaks will be passed. Therefore, the quality of the feature extraction is improved as indicates in Figure 6.

The features were extracted every 320 (one trial) for about 16 target trials. Although there is some noticeable improvement, it remains difficult to identify the associated signals with respect to the given stimulus. The extracted maximum amplitude with its frequency ranges about 7 to 30 Hz for each channel (O1, O2, and Oz) are given in Figure 8 and Figure 9 for Chebychev and Butterworth extraction methods, respectively. Each figure indicates that the maximum amplitude is achieved at the average frequency of 10 Hz (subject 4). The FFT results with Chebychev method is slightly better than obtained with Butterworth. However, these results were not automatically happened with all subjects. In several subjects, the obtained with Butterworth methods was better as indicated in Tables 1 to 4.

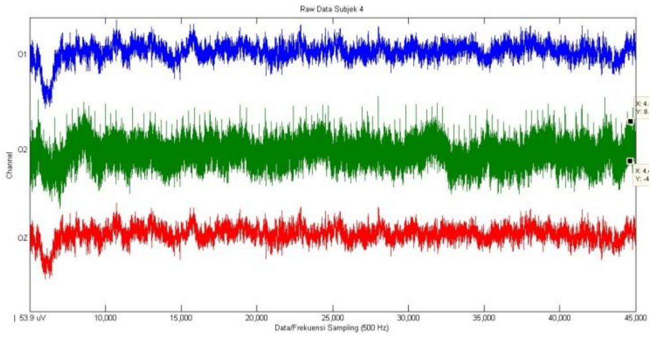

Figure 5: Raw data of EEG-SSVEP

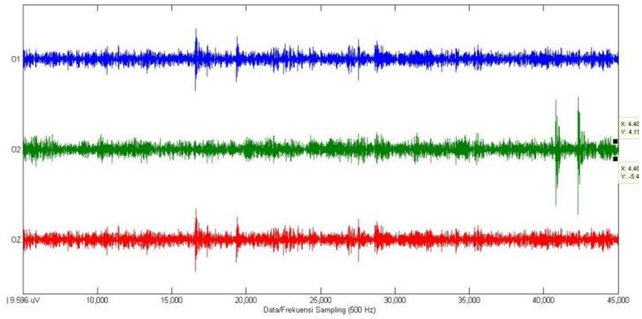

Figure 6: Extracted EEG-SSVEP signals with Chebyshev

The EEG-SSVEP signals have been converted from time domain to frequency domain by using the FFT method (Figures. 8 and 9), the value varies greatly from the three channels used. So a classifier is required that will produce a single value to navigate the electric wheelchair. To improve the learning process and produce high accuracy the number of neurons, the classifier is designed with 2 layers with the first layer 72 neuron and second layer 1 neuron. Training of an AFNN is the same as solving a nonlinear programming problem. The variables of the problem are the weights of the AFNN, and the objective function is the mean square error of all the training patterns. The error of an input pattern is the difference between the desired output and the actual output generated by the AFNN. The Levenberg-Marquardt curve-fitting method (a combination of two minimization methods: the gradient descent method and the Gauss-Newton method) is used.

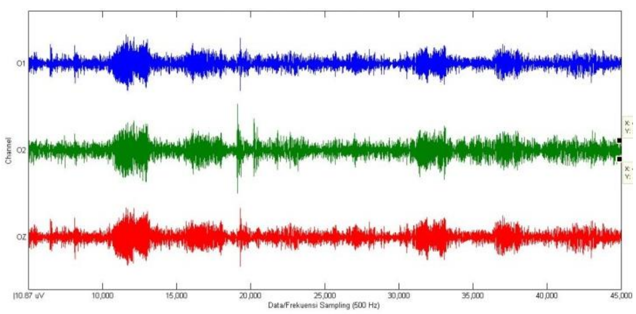

Figure 7: Extracted EEG-SSVEP signals with Butterworth.

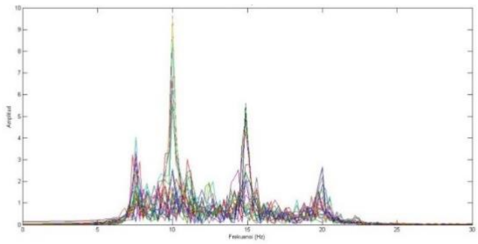

Figure 8: The captured signal in frequency domain from Chebyshev extraction

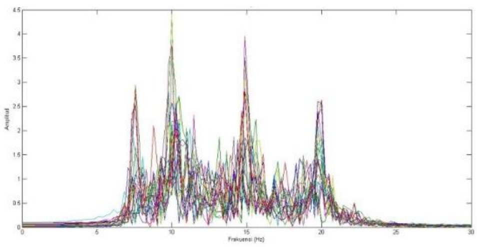

Figure 9: The captured signal in frequency domain from Butterworth extraction

The classification results for all subject are given in Table 1and Table 3 (left and right) using feature extracted by Chebchev method and Table 2 (forward and stop) using feature extracted by Butterworth. The average classification accuracy of 82% and 62.2% for Chebychev and Butterworth extraction method are achieved. The significant difference of classification accuracy between the obtained from Chebychev and Butterworth methods is caused by the wide range of the Butterworth stopband (i.e., 3-40 Hz). The passband range of the Butterworth is about 6 – 21 Hz. There were some noise or artifact that included in the extracted signals especially in the low and high-frequency range. This statement highly related with the low classification results in both frequency range (i.e., < 7.5 Hz and > 17.5 Hz) which related with left and stop direction. That low classification for the high-frequency range might be caused by the frequency of the stimulus were too high by mean the ability of visual concentration of most subject is less than 18 Hz. The higher classification accuracy of 100% and 85.7% for both methods are obtained for forward direction. It can be concluded that the classification accuracy is affected by the stimuli frequency and the design of the extraction method especially related to the range of the stopband.

Table 1
Classification Accuracy: Left and Right with Chebychev Method

S	Left (> 17.5Hz)				Right (12.51-17.5Hz)			
	Input			Out	Input			Out
	O_1	O_2	O_z		O_1	O_2	O_z	
1	20	20	20	20	14.9	14.9	14.9	15
2	11.7	18.4	17.7	17.6	13.4	12	13.4	15
3	19.8	19.8	19.8	19.4	14.9	14.9	14.9	15
4	20	9.76	20	20	14.9	14.9	14.9	15
5	9.76	10.2	9.76	**10**	15.1	14.6	15.1	14.2
6	11	10.5	11	**10.1**	14.9	15.1	14.9	16.3
7	17.56	15.1	17.56	17.8	14.9	15.1	14.9	16.3
8	7.56	18.9	7.56	17.9	14.9	14.9	14.9	15
9	14	7.56	14.4	**15**	12	12	14	13
10	10.2	10	10.2	**9.98**	15.1	14.9	15.1	15
11	15.1	9.76	15.4	18.9	14.9	14.9	14.9	15
12	20	11.2	20	20	14.9	11.5	14.9	13.6
13	15.1	7.65	19.1	18.3	10.5	9.27	8.54	**7.92**
14	12.9	10	12.9	**12**	15.6	14.9	15.6	15.1
	Accuracy			**64%**	Accuracy			**93%**

Table 2
Classification Accuracy: Forward and Stop with Chebychev Method

S	Forward (7.51-12.5Hz)				Stop (< 7.5Hz)			
	Input			Out	Input			Out
	O_1	O_2	O_z		O_1	O_2	O_z	
1	10	10	10	9.99	7.56	14.9	14.9	-12.6
2	14.6	12.2	14.6	12.4	13.2	12.9	13.2	**10.7**
3	10	10	10	9.99	14.9	7.56	14.9	7.2
4	10	14.6	10	11.7	14.9	7.56	5.9	7
5	11	11	11	9.99	11	11	11	**9.99**
6	10	10	10	9.99	4.4	8.9	12.4	5.5
7	10	10	10	9.99	9.76	10	9.76	**10**
8	10.2	7. 6	10.2	9.99	9.76	7.32	6.76	5.7
9	10.2	10	10.2	9.98	5	10	4	6.98
10	9.76	10	9.76	10	7.56	7.56	7.56	7.49
11	10	10	10	10	10	14.9	13.9	13.7
12	10	10	10	10	5.9	12.4	7.9	5.3
13	9.76	10	10	10.2	7.56	150.2	7.56	6.35
14	10	7.56	10	11.2	14.9	11.2	14.9	**14.2**
	Accuracy			**100%**	Accuracy			**71%**

Table 3
Classification Accuracy: Left and Right with Butterworth Method

S	Left (> 17.5Hz)				Right (12.51-17.5Hz)			
	Input			Out	Input			Out
	O_1	O_2	O_z		O_1	O_2	O_z	
1	20	11.2	20	20	14.9	14.9	14.9	15
2	11.7	12.4	11.7	**10**	13.4	12	13.4	15
3	20	12.7	20	20	14.9	11	14.9	15
4	19.8	9.76	20	20	14.9	14.9	14.9	15
5	4.88	12.9	5.12	**7.48**	11.7	12	11.7	**7.17**
6	11	22.2	11	17.6	11.2	15.1	11.2	14.5
7	6.1	6.34	5.85	**7.58**	5.85	6.34	5.85	**7.37**
8	7.56	8.78	7.56	**7.72**	7.32	7.56	7.32	**7.77**
9	**11**	11.5	18.5	19.1	10	10	10	**9.99**
10	5.61	14.4	5.61	**7.86**	15.1	14.9	15.1	15
11	12.9	9.76	12.9	18.9	11.7	14.9	14.9	14.6
12	11.2	11.2	20	**7.52**	14.9	22.9	14.9	17
13	11.7	4.88	11.7	31.5	12.9	7.32	8.54	**22.3**
14	12.9	4.88	12.9	31.3	15.6	12.4	15.6	17.3
	Average Accuracy			**57.1%**	Average Accuracy			**64.3%**

Table 4
Classification Accuracy: Forward and Stop With Butterworth Method

S	Forward (8.75-12.5Hz)				Stop (< 7.5Hz)			
	Input			Out	Input			Out
	O_1	O_2	O_z		O_1	O_2	O_z	
1	10	10	10	9.99	7.56	11	7.32	7.49
2	13.2	12.2	13.2	11.5	13.2	12.9	13.2	**10.7**
3	10	12.2	10	10	14.9	11.2	14.9	**14.6**
4	11	8.78	11	10	7.56	22.2	7.56	7.5
5	11	11	11	9.99	11	11	11	**10**
6	9.27	10	9.27	9.99	12.4	12.4	12.4	**10.3**
7	10	5.85	10	9.99	11	5.61	11	5.36
8	10.2	7.56	10.2	9.99	10.9	7.32	9.75	7.2
9	11.2	11	11	10	10.7	11	10.7	**9.98**
10	9.76	10	9.76	10	7.56	7.31	7.56	7.49
11	10	20	10	**5.57**	13.4	13.9	12.2	**9.83**
12	10	23.7	10	10.5	14.9	12.4	14.9	**19.3**
13	9.76	10	10	10.2	7.56	12.9	11.2	7.38
14	10	5.61	10	9.96	14.9	11.2	14.9	**14.2**
	Average Accuracy			**92.8%**	Average Accuracy			**42.6%**

IV. CONCLUSIONS

A non-invasive brain-computer interface uses EEG-SSVEP signals over visual cortex to control electronic wheelchair movement (i.e., Stop, forward, right, and left) is developed. A comparison of real-time extraction using the IIR Chebyshev of 4 order and the IIR Butterworth of 6 order methods is proposed. The total average classification accuracy of 82% and 62.2% for Chebychev and Butterworth extraction method are achieved. The higher average classification accuracy of 100% and 92.8% for both methods, respectively, are obtained for forward direction (8.75-12.5Hz). It can be concluded that the classification accuracy is affected by the stimuli frequency and the design of the extraction method especially related to the range of the stopband.

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