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RESEARCH PAPER

Frequency Domain Analysis to Identify Neurological Disorders from Evoked EMG Responses

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Abstract Evoked EMG M-responses obtained from the thenar muscle in the palm by electrical stimulation of the median nerve demonstrate a well-established smooth bipolar shape for normal healthy subjects. Kinks in this curve are observed in certain neurological disorders and preliminary work suggests their relationship to cervical spondylosis. The present work was taken up to develop an objective method for the identification of such neurological disorders for automated diagnosis by analysing the M-responses. A Fourier transform was performed using MATLAB, and features in the frequency domain were studied to distinguish healthy and smooth M-responses from ones with kinks. The features included some basic parameters like peak amplitude, peak frequency, frequency bandwidths, and areas in specified frequency segments. Ratio and deviation parameters from the above basic parameters were also studied to make 39 parameters in all. Out of these 10 came out as 'highly significant', 17 as 'significant' and the rest as insignificant, in statistical *t*-tests. A weighted combination of the significant parameters may allow identification of kinks with confidence.

Keywords CMAP · M-response · Nerve conduction · FFT · EMG · DCV

1 Introduction

Evoked EMG represents the compound muscle action potential (CMAP) produced by contracting muscle fibres on artificial stimulation of a nerve trunk supplying the muscle group. Traditionally a value of motor nerve conduction velocity (MNCV) is obtained from the onset latencies of direct evoked EMG (or M-responses) by stimulating the nerve at two distant points.

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There should be more diagnostic information hidden in the evoked EMG signal; however, so far as our knowledge goes, no attempts in this direction have been taken by any one except our group in Dhaka University [1–5]. Much has been done in the analysis of voluntary EMG [6–9] for extracting diagnostic information, on analyses of evoked nerve action potential in order to obtain estimates of distribution of conduction velocity (DCV) of nerve fibres [10–12], and on correlation of diseases or disorders with latency values of evoked EMG responses [13–15], but no one else attempted analyses on evoked EMG waveforms. Evoked EMG involves some uncertainties due to delays at the neuromuscular junctions [16], and possibly it is due to this reason that no one has attempted analysing these outputs from the human body.

The Biomedical Physics Group at Dhaka University has a long clinical experience of using evoked EMG signals for nerve conduction studies. Observing systematic patterns of these waveforms, this group felt that evoked EMG may be useful in extracting useful diagnostic information. Since the delays involved in the neuromuscular junctions would remain unchanged for a particular neuromuscular junction group of a particular subject, they argued, differences in the evoked EMG waveforms obtained from the same recording electrodes for two or more points of stimulation on the supplying nerve would be related only to the DCV of the nerve trunk. Therefore, there could be a possibility of extracting DCV information, at least grossly, from the evoked EMG waveforms obtained from several points of stimulation on the same nerve. Again, observing similar patterns of evoked EMG waveforms for different healthy normal subjects, they assumed that the statistical nature of the neuromuscular delays would be the same for all subjects, though varying in actual values from person to person, and that for neural disorders not involving neuromuscular junctions or muscle fibres, it may be possible to extract diagnostic information from evoked EMG responses. Initially this group performed synthesis of evoked CMAP through numerical simulation based on DCV and assumed gross disorders like fast fibre loss, slow fibre loss, middle fibre loss, etc. as a forward problem. Then they used these information to extract qualitative information on DCV from evoked CMAP. Through these attempts the group developed some insight into the underlying phenomena, and these are the subjects of the above mentioned five references [1–5].

For a normal healthy subject, the evoked CMAP from the abductor policis brevis muscle of the palm, supplied by the median nerve, has a smooth bipolar shape [16]. Based on the above mentioned simulation work the group has shown that kinks in this CMAP are a signature of neurological disorder, particularly related to loss of fibres in the mid-velocity range. This information may be useful for an objective analysis of neurological health. The group has also found evidence to relate these kinks to cervical spondylosis (CS) though further work is necessary to confirm this claim [17–20].

The present work was taken up to develop an objective method to identify such kinks in the CMAP using pattern recognition techniques, so that an automated diagnosis may be obtained. Since kinks in a smooth waveshape are expected to come from higher frequency components, the first method of choice in identifying such kinks is the Fourier transform which would give a description of the M-response in the frequency domain. In order to identify parameters in the frequency domain that can provide the desired objective tests, real life CMAPs were collected that represent both normal subjects (having smooth bipolar shape) and patients (having kinks). Sometimes a single parameter may not give reliable pattern recognition. So, in the present work, several parameters in the frequency domain were tried. If a number of parameters can be found which are individually identifiers of the above neurological disorder, then a combination of these could increase the confidence in the diagnosis. In order to perform the above tasks, digital signal processing (DSP) techniques were used and were implemented using MATLAB, a well-known mathematical software package [21]. Statistical *t*-tests were performed in order to ascertain the parameters that could distinguish the two groups significantly.

2 Methods

Computerised EMG equipment designed and fabricated locally by a joint collaboration of the Bio-Medical Physics Group, University of Dhaka and Bangladesh Institute of Biomedical Engineering and Appropriate Technology (BiBEAT), a non-profit, non-governmental organisation, has been in use since 1988 for providing routine clinical service for nerve conduction and for research. Initial design expertise was obtained through a British collaboration [22]. The evoked CMAP data from median nerve used for this study were chosen from those obtained previously with this facility. Based on the shapes the median nerve CMAP data were classified into three groups as follows.

Group A: having standard smooth bipolar shape, which relates to normal healthy nerve (number of subjects: 14)

Group B: having kinks in the CMAP response, reflecting neurological disorders with the possible loss of mid-velocity fibres, as mentioned before (number of subjects 22)

Group C: having shapes different from either of the above.

Only data from Group A and Group B were considered for the present pattern recognition work. Group C is for other disorders which we have not classified as yet. Therefore these results were not subject to any analysis in the present work. The aim of the present work is to identify some parameters that can distinguish Group B from Group A quantitatively. Typical shapes of CMAPs, falling into the two chosen groups, are shown in Fig. 1.

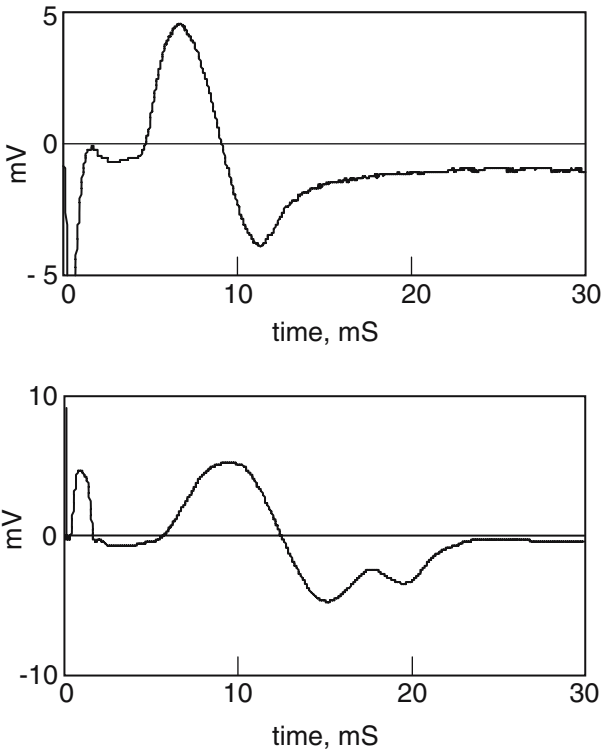

Fig. 1 Typical M-responses from median nerve without kink (*top*) and with kink (*bottom*)

It can be anticipated that kinks in the CMAPs will contribute to higher frequency components in the frequency spectrum, so, all the CMAPs were first transformed into frequency domain using FFT algorithm. Since the CMAPs are already available in discrete-time sequence form, Fourier analyses were carried out directly. If N is the number of sample points of the discrete-time sequence $x[n]$, and Δt is the sampling interval; the corresponding frequency f_k of the transformed signal is given by

$$f_k = \frac{kF_s}{N}, \tag{1}$$

where, $F_s = 1/\Delta t$ is the sampling frequency and k=0, 1, 2, ..., $N-1$ is the index number in the frequency domain. In the present study the sampling interval for some of the data sets was 25 μs while for the rest it was 40 μs. The number of sample points were 512 for all the samples.

From a Fourier transformed signal, the following parameters may be obtained:

1) Amplitude spectrum with real and imaginary parts of the amplitude separately
2) Absolute value spectrum of the amplitude
3) Phase spectrum

In the present study only the absolute value spectrum of the amplitude has been chosen for frequency domain analyses. The parameters of the transformed signal in the frequency domain that have been tried initially for analyses are as follows, the symbols used to represent them being given in brackets.

a. Peak Amplitude (A_p)
b. Peak Frequency (f_p)
c. Frequency Width at 10% of A_p ($\Delta f_{10\%}$)
d. Frequency Width at 50% of A_p ($\Delta f_{50\%}$)
e. Frequency Width at 90% of A_p ($\Delta f_{90\%}$)
f. Area under the curve from 0 to 2 kHz (a_{0-2})
g. Area under the curve from 2 to 5 kHz (a_{2-5})

The parameters c to g essentially was chosen to separate the high frequency components from the low frequency ones. The area under specified regions of the curves were calculated using the trapezoidal integration rule. Based on the above parameters, the following ratio parameters were evaluated:

1) $R_{10/90} = \frac{\Delta f_{10\%}}{\Delta f_{90\%}}$
2) $R_{10/50} = \frac{\Delta f_{10\%}}{\Delta f_{50\%}}$
3) $R_{10/p} = \frac{\Delta f_{10\%}}{f_p}$
4) $R_{50/p} = \frac{\Delta f_{50\%}}{f_p}$
5) $R_{90/p} = \frac{\Delta f_{90\%}}{f_p}$
6) $R_a = \frac{a_{0-2}}{a_{2-5}}$

In an MNCV measurement of the median nerve, CMAPs are usually obtained for stimulation at two points on the nerve, typically at the wrist (distal) and at the elbow (proximal) giving two conduction distances. For the longer conduction distance the individual nerve fibre action potentials get more dispersed in time so the CMAP would have different patterns in the frequency domain compared to that for a short conduction distance. The above parameters were separately evaluated for responses obtained from both

distal and proximal stimulations for both Group A and Group B. Deviations of the above parameters in the frequency domain for two such conduction distances may also provide significant clues to separate the two groups considered in this study. The following deviation parameters between corresponding distal and proximal parameters were also evaluated and analysed.

1) $\delta A_p = \left|A_{p,\text{distal}} - A_{p,\text{proximal}}\right|$
2) $\delta f_p = \left|f_{p,\text{distal}} - f_{p,\text{proximal}}\right|$
3) $\delta f_{10\%} = \left|\Delta f_{10\%,\text{distal}} - \Delta f_{10\%,\text{proximal}}\right|$
4) $\delta f_{50\%} = \left|\Delta f_{50\%,\text{distal}} - \Delta f_{50\%,\text{proximal}}\right|$
5) $\delta f_{90\%} = \left|\Delta f_{90\%,\text{distal}} - \Delta f_{90\%,\text{proximal}}\right|$
6) $\delta a_{0,2} = \left|a_{0,2\text{distal}} - a_{0,2\text{proximal}}\right|$
7) $\delta a_{2,5} = \left|a_{2,5\text{distal}} - a_{2,5\text{proximal}}\right|$
8) $\delta R_{10/90} = \left|R_{10/90,\text{distal}} - R_{10/90,\text{proximal}}\right|$
9) $\delta R_{10/50} = \left|R_{10/50,\text{distal}} - R_{10/50,\text{proximal}}\right|$
10) $\delta R_{10/p} = \left|R_{10/p,\text{distal}} - R_{10/p,\text{proximal}}\right|$
11) $\delta R_{50/p} = \left|R_{50/p,\text{distal}} - R_{50/p,\text{proximal}}\right|$
12) $\delta R_{90/p} = \left|R_{90/p,\text{distal}} - R_{90/p,\text{proximal}}\right|$
13) $\delta R_a = \left|R_{a,\text{distal}} - R_{a,\text{proximal}}\right|$

In order to identify the parameters that may distinguish Group B from Group A, the mean and an unbiased estimate of standard deviation (σ_{n-1}) were calculated for each of the above parameters and *t*-tests were performed. In a usual two-tailed test the significance level is usually taken at $P<0.05$, and it is taken to be highly significant if $P<0.01$. Since the nerve conduction parameters are essentially one tailed – a parameter is abnormal if it is either higher, or lower than a certain critical value – a difference was taken to be significant (S) if $P<0.1$, and highly significant (H) if $P<0.02$. Another category, 'tending to be significant' (T), was chosen for $P<0.2$ and for greater values they were termed insignificant (I).

3 Results and Observations

The absolute value spectrum of M-responses for both distal and proximal stimulation, obtained using FFT, of two typical samples each from Group A (Subjects A1 and A2) and Group B (Subjects B1 and B2) are shown in Fig. 2. It can be seen that those from Group B, having kinks in their M-responses, have higher frequency components than Group A, as expected, and this would have an important bearing on the results to be discussed below.

Table 1 presents values of some of the chosen parameters in the frequency domain and the results of the tests of significance in order to distinguish Group B from Group A. This table uses the data for distal stimulation with 14 subjects in Group A and 22 subjects in Group B. Table 2 presents the same for proximal stimulation for the same subjects. More parameters in the proximal case appear to be significant compared to that for the distal case. This is somewhat expected since in the proximal case, the action potentials conduct over a longer distance along the nerve allowing individual components in each fibre to become more dispersed in time. The highly significant parameters common in both the cases are $f_{10\%}$ and $R_{10/50}$ while in the proximal case $a_{2,5}$, $R_{10/90}$ and R_a are also highly significant. The frequency width at 10% of the peak amplitude, $f_{10\%}$, is expected to be large if high frequency components are present, and therefore, is one of the major parameters in identifying the kink. By the same token, the insignificance of $f_{90\%}$ is expected as it only

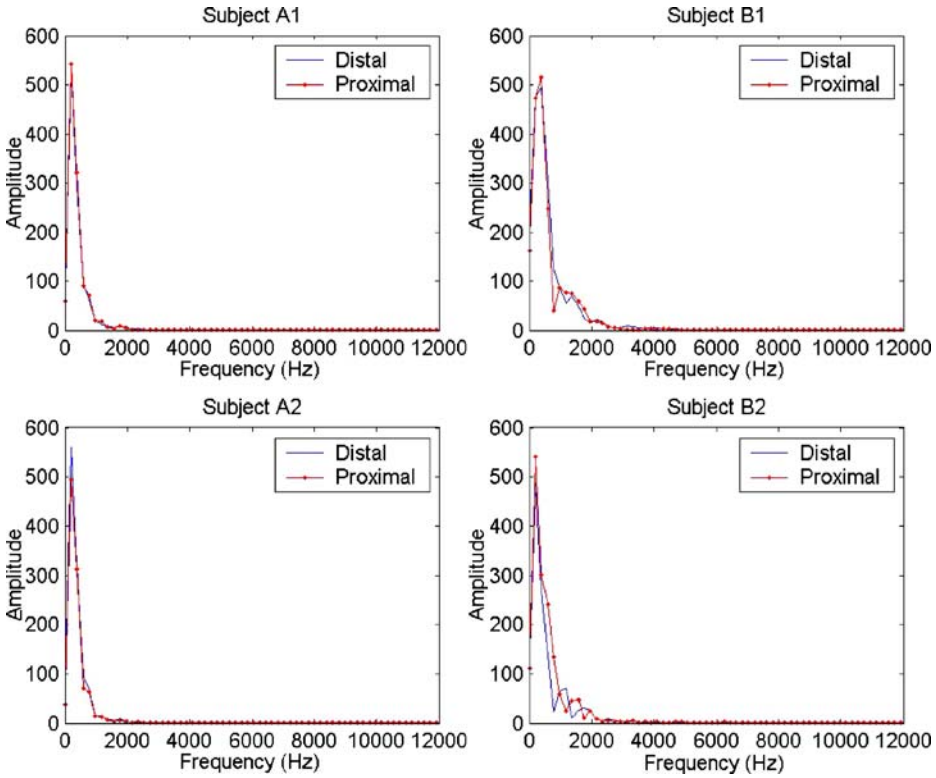

Fig. 2 Typical Fourier transform of M-response for both distal and proximal stimulation (from subjects A_1, A_2: without kink and B_1, B_2: with kink)

Table 1 Test of significance for distal parameters

Parameter	Group A, n_a=14		Group B, n_b=22		t value	P	Remarks
	Distal		Distal				
	Mean	S.D.	Mean	S.D.			
A_p	908.16	312.42	718.28	317.07	1.767	0.1	T
f_p	709.45	127.13	810.79	161.68	2.093	0.05	S
$f_{10\%}$	2790.21	515.96	3623.95	846.01	3.672	0.0005	H
$f_{50\%}$	1215.61	154.23	1367.86	291.25	2.0423	0.025	S
$f_{90\%}$	292.18	122.65	305.05	134.58	0.295	0.4	I
$a_{0,2}$	1.11E+06	3.85E+05	9.51E+05	4.15E+05	1.169	0.25	I
$a_{2,5}$	1.94E+05	7.35E+04	2.32E+05	9.19E+04	1.357	0.1	T
$R_{10/90}$	10.41	2.73	13.01	3.92	2.344	0.025	S
$R_{10/50}$	2.3	0.32	2.71	0.64	2.547	0.01	S
$R_{10/p}$	4.03	1.02	4.6	1.25	1.495	0.1	T
$R_{50/p}$	1.78	0.47	1.74	0.44	0.254	0.45	I
$R_{90/p}$	0.44	0.25	0.38	0.15	0.81	0.25	I
R_a	6.08	1.86	4.47	2.43	2.245	0.025	S

H Highly significant; *S* significant; *T* tending to be significant; *I* insignificant

Table 2 Test of significance for proximal parameters

Parameter	Group A, n_a=14		Group B, n_b=22		t value	P	Remarks
	Proximal		Proximal				
	Mean	S.D.	Mean	S.D.			
A_p	851	340.54	680.56	274.21	1.575	0.1	T
f_p	687.38	114.14	773.32	152.25	1.93	0.05	T
$f_{10\%}$	2680.71	374.15	3377.36	834.5	3.413	0.001	H
$f_{50\%}$	1254.46	209.87	1242.77	279.79	0.142	0.5	I
$f_{90\%}$	339.44	196.67	272.86	130.5	1.12	0.25	I
$a_{0,2}$	1.08E+06	3.98E+05	8.23E+05	3.19E+05	2.036	0.05	S
$a_{2,5}$	1.45E+05	7.29E+04	2.25E+05	1.15E+05	2.554	0.01	H
$R_{10/90}$	9.45	3.11	13.83	3.49	3.928	0.0005	H
$R_{10/50}$	2.16	0.28	2.79	0.64	4.064	0.0005	H
$R_{10/p}$	3.98	0.74	4.47	1.11	1.59	0.1	T
$R_{50/p}$	1.89	0.51	1.63	0.4	1.619	0.1	T
$R_{90/p}$	0.53	0.36	0.34	0.1	1.927	0.05	T
R_a	8.29	3.14	4.31	1.88	4.28	0.0005	H

H Highly significant; *S* significant; *T* tending to be significant; *I* insignificant

contains mostly the low frequency components, which would almost be the same in both the groups. Again, the area under the curve within a high frequency band as for $a_{2,5}$ is expected to show up in the difference, which it has done, by being highly significant in the proximal case, and significant in the distal case. As a first consideration, the peak frequency f_p would be a good candidate in distinguishing the two groups. However, since its value depends on the combination of all the frequency components, this would soften the distinction, as has been demonstrated through this parameter being significant, but not highly significant, in both the cases. The amplitude of the peak, A_p, has diminished in Group B, which is again expected since the peak appears at a relatively low frequency zone while a kink in the

Table 3 Test of significance for deviation parameters

Parameter	Group A, n_a=14		Group B, n_b=22		t value	P	Remarks
	Mean	S.D.	Mean	S.D.			
δA_p	80.74	62.52	105.8	139.3	0.735	0.25	I
δf_p	30.55	16.86	37.47	39.61	0.722	0.25	I
$\delta f_{10\%}$	165.79	143.12	393.59	351.14	2.709	0.10	S
$\delta f_{50\%}$	44.56	66.08	148.55	111.18	3.518	0.001	H
$\delta f_{90\%}$	49.11	76.9	34.27	27.29	0.694	0.25	I
δa_{0-2}	7.18E+04	4.09E+04	1.75E+05	1.86E+05	2.509	0.01	S
δa_{2-5}	5.23E+04	4.49E+04	6.57E+04	7.08E+04	0.695	0.25	I
$\delta R_{10/90}$	3.27	3.12	1.98	1.88	1.39	0.10	T
$\delta R_{10/50}$	0.46	0.57	0.34	0.31	0.722	0.25	I
$\delta R_{10/p}$	0.95	1.35	0.47	0.46	1.29	0.25	I
$\delta R_{50/p}$	0.49	0.49	0.18	0.14	2.318	0.025	S
$\delta R_{90/p}$	0.26	0.26	0.06	0.09	2.8	0.005	H
δR_a	4.37	2.53	1.75	1.88	3.33	0.0025	H

H Highly significant; *S* significant; *T* tending to be significant; *I* insignificant

original time domain response would shift some of the components to higher frequencies. Besides, the number of nerve fibres contributing to the response cannot be greater in disease than in normal health.

Table 3 presents the deviation parameters obtained from responses due to proximal and distal stimulations. There are three highly significant parameters and four significant parameters. The causes behind these parameters depend on several factors and explanations are not so straightforward. The significance for $\delta f_{10\%}$ and $\delta f_{50\%}$, with a high significance for the latter, but the insignificance of $\delta f_{90\%}$ indicates that the contribution of kinks in the dispersion due to distance is around the middle region in the frequency domain, with a less significant contribution at the high end.

4 Discussion

The basic motivation of the present work is to provide an objective diagnosis of neural disorders using evoked EMG responses directly, which can be easily recorded. M-responses from the thenar muscles in the palm, served by median nerve, were used since their normal shapes are well known, which usually is a smooth bipolar one. M-responses having kinks were found to be associated with neural disorders, and a preliminary work by the authors' group indicates that it may relate to cervical spondylosis, a very common disorder. Kinks are associated with high frequency components, and thus, 13 frequency-domain parameters were chosen for this study, with an expectation that some of these may bring forth a pattern, which may be useful in identifying the M-responses with kinks. These included some basic parameters like peak amplitude, peak frequency, and frequency bandwidth at 90%, 50% and 10% of the peak amplitude, area under the curve in a low frequency segment and in a high frequency segment. The derived parameters constituted of the ratios between some of the above basic parameters. Again the above parameters were evaluated for M-responses obtained for two conduction distances, here for a distal stimulation site at the wrist, and a proximal stimulation site at the elbow. As the individual fibre components of the total nerve action potentials get more time for dispersion in the proximal case, this offered an additional 13 parameters for a different conduction distance and a further 13 deviation parameters between pairs of corresponding values for study. Some of the parameters showed significant differences that can be a basis of an objective test.

Rather than relying on a single parameter, this work targets many, so that a weighted combination of these parameters would increase the confidence in the diagnosis. Use of digital signal processing (DSP) techniques and MATLAB, a well known mathematical software package, has made the analyses simpler.

Segregation of the data into different groups was tricky. Particularly, the selection of healthy normal data under Group A had to be done under some constraints. Not many data sets were available which matched the perfect assumed shape and values of latency and NCV that were assumed to represent a normal data set. Therefore some data sets demonstrating smooth wave shape but deviating slightly from the expected behavior were also included in this graph. The data sets from Group B were rather easier to choose, since they had to have kinks somewhere in the response. The rest that had abnormal wave shape or abnormal distal latency and NCV were classified under Group C, and these data were not used in the work. There may be different pathological causes behind the abnormalities demonstrated in Group C for which further work is necessary. However, if the causes and features are identified in future, these data may be used for further automated analysis as well.

Altogether, 39 parameters were studied with statistical tests in this study. Out of these parameters, 10 were found to be highly significant, 17 were found to be significant and the remaining 12 were insignificant. A weighted combination of the significant and highly significant parameters may possibly increase the chances of identifying the neurological complaint manifold. A possible technique would be to use a neural network with appropriate weights. Furthermore the position of the kinks in the M-response in time domain may provide further information, regarding the type of neural pathology. Application of other numerical techniques like the wavelet transform may be attractive in this regard [9].

The present work is very significant in that it has targeted development of an objective method to identify kinks in the M-responses using computational techniques, so that an automated diagnosis may be obtained for such neurological disorders. Although further work is necessary to establish the specific disorders that the kinks represent, the present work may be useful in an automated system to isolate such cases. As mentioned before, there is a possibility of relating these kinks to cervical spondylosis (CS), a disorder leading to the disability of a great number of people globally. If that happens, then the present work would make a very attractive alternative for its diagnosis.

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