Extended Upscale and Downscale Representation with Cascade Arrangement

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***Abstract*—Smoothing filters are widely used in EEG signal processing for noise removal while preserving important features. Unlike common approaches in the time domain, a recent effective algorithm using the Upscale and Downscale Representation (UDR) technique has been introduced to process the signal in the image domain. The idea of UDR is to visualize the input with an appropriate line width, convert it to a binary image, and then smooth it by skeletonizing the signal object to a unit width and projecting it back to the time domain. We propose in this paper a cascaded UDR (CUDR) where the interested signal is filtered twice. CUDR's performance is verified on simulated data with added white Gaussian noise and compared with the cascaded arrangement of some conventional techniques. Experimental results have demonstrated the outperformance of CUDR in terms of the fitting error when dealing with noisy signals, especially at a low signal-to-noise ratio.**

***Index Terms*—Smoothing, thinning, skeletonization, electroencephalogram (EEG), signal processing, time-series, noise, filter**

I. Introduction

Electroencephalogram (EEG) is widely used for clinical diagnosis and monitoring to detect brain disorders [1], [2] as well as in Brain-Computer Interface (BCI) applications [3], [4]. One of common practices in EEG signal processing for specific pattern detection is via the visual inspection and interpretation of neurologists [5]. Therefore, the higher the EEG signal quality, the more promising results can be expected. Hence, EEG signal noise reduction becomes a vital aspect of EEG signal processing.

Many fields of engineering and science can benefit from the use of smoothing filters [6] [7], including computer vision [8], signal processing [9], and time series analysis [6], [10]–[13]. EEG signal processing is no exception when various smoothing filters have been developed for noise reduction. Some conventional filters applied to EEG signal smoothing are Moving Average, Savitzky-Golay [14], and Binomial Filter. Unlike these algorithms that filter out the signal in the time domain, a recent effective approach in the image domain, UDR, has been proposed [21]. The concept behind UDR is to visualize the input signal at a suitable line width and convert it to a binary image. After that, the signal object is skeletonized to a unit width and projected back into the time domain. The quantitative results in [21] have shown the promising capability of UDR on noise removal in EEG signals.

It has been pointed out in [15] that a successive two-stage filter can significantly increase the smoothing results. In fact, cascade arrangements of conventional filters have been implemented widely to increase the filter effectiveness. For instance, a four-stage cascaded Savitzky-Golay filter is developed in [16] to eliminate noises like powerline interference (PLI) from the ECG signals. The two-layered hierarchical cascaded Moving Average filter is utilized to evaluate and remove the baseline wander from the raw vibro-arthrography (VAG) signal [17]. An adaptive filter model with a cascaded structure is presented in [18] for noise reduction in speech signals of Parkinson's disease (PD) patients. In EEG signal processing, a cascaded Savitzky-Golay is introduced in [15] to improve the noise removal ability of the Savitzky-Golay filter in EEG signals. In this paper, a cascaded UDR is developed to evaluate the enhancement of UDR when applying the cascaded arrangement.

The rest of the paper is structured as follows. The overview of the smoothing algorithm using Upscale and Downscale Representation (UDR) and the idea of cascaded UDR (CUDR) are described in Section II. The employed data and evaluation metrics are declared in Section III. Results of the extended UDR and some comparative smoothing filters are reported in Section IV. Finally, the discussion and conclusion are presented in Sections V and VI.

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II. Methodology

A. Overview on Smoothing Algorithm Using Upscale and Downscale Representation (UDR)

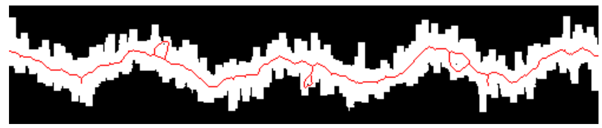
The idea of upscaling in UDR is inspired by the "zoom in" process when neurologists visually inspect signals for peak labeling on EEG peak detection in cognitive conflict processing [19], [20]. Let X be the signal to be processed, W, and T_W correspondingly be the line width of plotted signal, the line width threshold value, respectively. The noisy signal is first graphically visualized with the initial line width W in a figure. Then, the figure is converted into a binary image. A unit-width curve representing the signal is generated from the binary image by applying a thinning algorithm. Finally, the skeletonized curve is projected back to the time domain. As reported in [21], UDR outperforms other conventional filters in the task of removing noise from simulated data. Besides, the experiment on a real EEG dataset also shows promising results in a signal classification task. The pseudocode of UDR is presented in Algorithm 1.

A disadvantage of UDR is its human intervention dependence. Indeed, the line width W must be adjusted while performing UDR until the correlation is maximum. With different signal durations, UDR requires a parameter set that generates the best-smoothed signal. As per our observation, UDR using a low line width can result in a waveform similar to the original signal with some unwanted noise. Although using a thicker line width can return a smoother skeleton, the waveform of which is flatter where some peaks are not preserved. Therefore, a cascaded UDR is proposed where a low W is implemented in the initial stage for waveform perseverance and a high W is employed in the second stage for signal smoothing. The idea is presented in Section II.B and verified in Section IV.

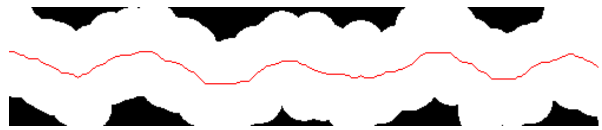
Algorithm 1 UDR

Input: X, W, T_W
Output: Y
  while $W \leq T_W$ **do**
    $F \leftarrow$ Plot X at W
    $B \leftarrow$ convert F to binary image
    Skel $\leftarrow$ skeletonize B
    $Y \leftarrow$ project *Skel* back to time domain
    $W \leftarrow$ adjust W
  end while

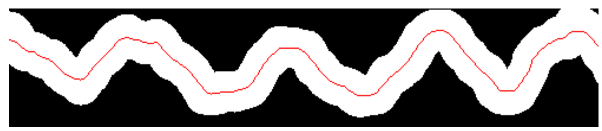
(a) Original signal



(b) UDR ($W = 5$)



(c) UDR ($W = 30$)



(d) CUDR ($W_1 = 10$ and $W_2 = 25$)

Fig. 1: Skeletonization on a signal using UDR and CUDR: white area is the plotted signal, red line is the generated skeleton

B. Cascaded Smoothing Algorithm Using Upscale and Downscale Representation

The two-stage or cascaded Savitzky-Golay smoothing filter (CSG) for biomedical signal processing is introduced in [15] to reduce signal distortion. As reported in [15], CSG worked better in signal denoising compared to other filters: Cascaded Moving Average (CMA), Cascaded Savitzky-Golay with Moving Average (CSGMA), Cascaded Savitzky-Golay with Binomial filter (CSGB) and single-stage Savitzky-Golay (SG), even in very noisy level (SNR = -5dB). Inspired by the ideas in [15] and [21], a cascaded arrangement of UDR is developed in this work to verify its performance in signal smoothing. Here, the input signal is filtered by going through successive UDRs using different line width values at each stage.

In UDR, the skeleton generated from the binary image is impacted by the level of the signal noise. Fig.1a illustrates the binary image of an extremely noisy signal epoch. Fig. 1b illustrates the binary image of UDR skeletonization in the noisy signal epoch, the skeleton of which consists of unwanted branches. This branch issue can be removed by using an appropriate thinning threshold, or increasing the line width W. Both approaches require human intervention and limit the automation of the algorithm, yet to mention the additional computational burden. Fig.1c illustrates the effectiveness of UDR at a higher value of W, although the processing time is also increased in this case. Here, a cascade arrangement of UDR is proposed where the input signal is processed through two successive stages with different line width values W. The input signal is first represented at a lower W and smoothed in the former, the result of which is then represented at a higher W and smoothed in the latter. Fig.1d illustrates the result of the proposed CUDR where the line width values are correspondingly selected as 10 and 25 at the first and second stages. It can be seen that the waveform is well preserved while the line width is not required to go up to 30 as shown in Fig.1c to reach a desired performance.

III. Data and Evaluation Metrics

A. Data

Let P_X, P_S be respectively the power of an input signal X and the white Gaussian noise n, by which X is distorted with. The signal-to-noise ratio (*SNR*) is defined as

$$SNR = \frac{P_X}{P_n}. \tag{1}$$

In this work, a multi-component signal dataset is generated to evaluate the enhancement of the proposed algorithm compared to the original UDR. Each component is defined as

$$S(t) = X(t) + n(t), \tag{2}$$

where n(t) is white Gaussian noise at SNR of -10, -5, -1, 1, 5, and 10 dB, and $X(t)$ is the synthetic signal as introduced in [22]. There are seven signal components which are described as follows:

component 1:

$$X_1(t) = 0.5\cos(\pi t) + 1.5\cos(4\pi t) + 4\cos(5\pi t), \tag{3}$$

component 2:

$$X_2(t) = 0.7\cos(\pi t) + 2.1\cos(4\pi t) + 5.6\cos(5\pi t), \tag{4}$$

component 3:

$$X_3(t) = 1.5\cos(2\pi t) + 4\cos(8\pi t), \tag{5}$$

component 4:

$$X_4(t) = 1.5\cos(\pi t) + 4\cos(4\pi t), \tag{6}$$

component 5:

$$X_5(t) = 0.5\cos(\pi t)+1.5\cos(2\pi t)+0.8\cos(3\pi t)+3.5\cos(5\pi t), \tag{7}$$

component 6:

$$X_6(t) = 4.5\cos(3\pi t) + 2.2\cos(5\pi t), \tag{8}$$

component 7:

$$X_7(t) = 0.8\cos(\pi t) + \cos(3\pi t) + 3\cos(5\pi t). \tag{9}$$

Then, these signal components are concatenated in random orders and duration from 2.75 to 4 s. In this work, 5040 concatenated signals were generated as permutations without repetitions of seven aforementioned components and employed as the evaluation dataset. In reality, an EEG signal also has different waveforms at different amplitudes and frequencies. Hence, this arrangement is to ensure the perseverance of the vital characteristics of the real-EEG signal [15].

TABLE I: COMPARATIVE FILTERS

Filters	**Order**	**Span/ Binomial coeficients**
Bionomial Filter (*BF*) [15]	N/A	21
Savitzky-Golay (*SG*) [15]	8	21
Moving average (*MA*) [15]	N/A	21
Cascaded Filters	**Stage 1**	**Stage 2**
SG-BF [15]	*SG*	*BF*
CSG [15]	*SG*	*SG*
SG-MA [15]	*SG*	*MA*
CMA [15]	*MA*	*MA*
UDR Filters	**W1**	**W2**
UDR	10	N/A
CUDR	10	25

B. Evaluation Metrics

Let Y be the smoothed signal, the Root Mean Square Error (*RMSE*) and the Correlation Coefficient (*COR*) evaluating the correlation between the input and the output are defined as

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}(X_k - Y_k)^2}{N}}, \tag{10}$$

$$COR = \frac{1}{N-1}\sum_{k=1}^{N}(\frac{X_k - \mu_X}{\sigma_X})(\frac{Y_k - \mu_Y}{\sigma_Y}), \tag{11}$$

where μ and σ are the mean and standard deviation of the signal, N is the number of data points in the observed interval.

For each concatenated signal $X(t)$, a noisy signal, called $S(t)$, is randomly generated by adding $n(t)$ to $X(t)$. The *RMSE* and *COR* between the input $X(t)$ and the smoothed signal $Y(t)$ are calculated to evaluate the effectiveness of the proposed approach compared to other techniques. The lower the RMSE and/or the higher the COR, the better the performance of the smoothing filter, and vice versa.

IV. Results

1) Comparative Algorithms: Table I shows the comparative filters used in this work for evaluation of the performance of CUDR on the test dataset. There are nine smoothing filters: four single-stage and five cascaded ones, which are recommended in [15].

2) Results on Simulated Data: The average results of non-cascaded comparative algorithms and CUDR on the test dataset are reported in Table II, which has confirmed not only the notable performance of UDR compared to other single-stage filters but also the significant enhancement compared to UDR.

As reported in Table II, if disregarding CUDR, UDR returns better results than other filters at four out of six *SNR* levels. At *SNR* from -1 dB to 10 dB, UDR has an average *RMSE* greater than the second-best time-domain filter from 0.88% at *SNR* = 10 dB to 9.6% at *SNR* = 5 dB. The comparison in terms of *COR* between UDR and the second-best time-domain filter at these *SNR* levels are from 0.05% at *SNR* = 10

TABLE II: AVERAGE RESULTS OF COMPARATIVE NON-CASCADED ALGORITHMS ON TEST SIGNALS

SNR	Metrics	*BF*	*SG*	*MA*	*UDR*	*CUDR*
-10	*RMSE*	3.5749	5.5188	2.2640	2.3667	**1.9833**
	COR	0.6595	0.5004	0.8103	0.7974	**0.8390**
-5	*RMSE*	2.0643	3.1036	1.3462	1.3512	**1.1819**
	COR	0.8354	0.7168	0.9188	0.9187	**0.9350**
-1	*RMSE*	1.3748	1.9584	0.9432	0.8827	**0.8152**
	COR	0.9160	0.8523	0.9577	0.9634	**0.9692**
1	*RMSE*	1.1450	1.5558	0.8151	0.7234	**0.6931**
	COR	0.9395	0.8989	0.9679	0.9752	**0.9784**
5	*RMSE*	0.8457	0.9820	0.6576	**0.5041**	0.5331
	COR	0.9657	0.9558	0.9788	0.9881	**0.9884**
10	*RMSE*	0.6676	0.5530	0.5722	**0.3607**	0.4439
	COR	0.9782	0.9853	0.9839	**0.9939**	0.9927

TABLE III: AVERAGE RESULTS OF COMPARATIVE CASCADED ALGORITHMS ON TEST SIGNALS

SNR	Metrics	*SG-BF*	*CSG*	*SG-MA*	*CMA*	*CUDR*
-10	*RMSE*	3.5622	5.1858	2.2299	2.0655	**1.9833**
	COR	0.6608	0.5239	0.8145	0.8245	**0.8390**
-5	*RMSE*	2.0574	2.9164	1.3281	1.4340	**1.1819**
	COR	0.8363	0.7381	0.9207	0.9036	**0.9350**
-1	*RMSE*	1.3706	1.8403	0.9329	1.2004	**0.8152**
	COR	0.9165	0.8663	0.9585	0.9299	**0.9692**
1	*RMSE*	1.1419	1.4620	0.8076	1.1361	**0.6931**
	COR	0.9398	0.9091	0.9685	0.9367	**0.9784**
5	*RMSE*	0.8440	0.9229	0.6539	1.0658	**0.5331**
	COR	0.9658	0.9606	0.9790	0.9439	**0.9884**
10	*RMSE*	0.6669	0.5198	0.5710	1.0325	**0.4439**
	COR	0.9783	0.9870	0.9839	0.9472	**0.9927**

dB to 0.73% at *SNR* = 1 dB. At lower level of *SNR* ({5,-10} dB), the outperformance of UDR is no longer maintained. The quantitative results in Table II indicate the difference between UDR, now ranked the second best, and the best (MA) is -0.5% to -10.27% in *RMSE* and -0.01% to -1.29% in *COR*.

As discussed, much human intervention is required to maintain the performance of UDR at low *SNR* levels, hence the development of CUDR. Table II shows the significant enhancement of CUDR over UDR at low *SNR*s ({-10, -5, -1, 1} dB). At these *SNR* levels, compared to UDR results, CUDR enhances 3.03% to 38.34% in *RMSE*, and 0.32% to 4.16% in *COR*. However, the effectiveness of CUDR did not happen at the higher SNRs (5 and 10 dB) as UDR did. The difference between CUDR and UDR at those noise levels is -8.32% to -2.9% in *RMSE* and -0.12% to 0.03% in *COR*. These results show that although CUDR could enhance UDR at low *SNR*s, it does not perform as good as UDR at higher *SNR*s.

Table III shows the comparison between cascaded smoothing algorithms. Notably, CUDR has outperformed the participating filters in all *SNR* levels. Indeed, CUDR is better than the second-best from 7.59% to 14.62% in *RMSE* and 0.57% to 1.45% in *COR*. The enhancement of other participating cascaded filters compared to the single stage one is not much, except CSG, as similarly verified in [15]. Besides, CMA even decreases the effectiveness of the origin filter (MA) in the test.

Although CUDR has outperformed other cascaded arrangements of participating filters and enhanced the performance of UDR at low *SNR* levels, the algorithm currently has some processing time limitations. Due to the cascaded arrangement, UDR is employed twice, leading to higher computational burden. The processing time of participating filters in a concatenated signal are shown in Table IV. This experiment was performed on an Intel(R) Core(TM) i9-10900 CPU @ 2.80GHz with 64GB RAM and GPU NVIDIA GeForce GTX 3090 using MATLAB 2021 for Ubuntu 20.04.5 LTS.

TABLE IV: PROCESSING TIME COMPARISON

Signal	Algorithms	Duration (ms)	Sampling rate (Hz)	Processing time (ms)
concatenated	BF	25000	1000	0.196
	SG			0.234
	MA			0.148
	SG-BF			0.443
	CSG			0.359
	SG-MA			0.393
	CMA			0.183
	UDR			507.511
	CUDR			2282.644

V. Discussion

The experiment results in this work have confirmed the UDR performance and demonstrated the promising potential of a vision-based filter in signal smoothing. This work has also indicated the limitation of UDR in very noisy signals and proposed an enhanced version, the CUDR. Indeed, the signal smoothing ability compared to UDR at low *SNR* levels has been significantly increased. For instance, at the noisiest level (*SNR* = -10 dB), CUDR is the only filter returning *RMSE* under 2, outrunning the second-best (CMA) at 1.45% in terms of *COR*. The reasons resulting in the out-performance of CUDR is the cascaded arrangement with two different line width values at each stage to take advantage of the original UDR while overcoming its limitation. When the noisy signal is plotted with small line width at the first stage, the waveform of the original signal is preserved. At the cascaded stage with a higher line width, the immediate result is smoothed, outputting the filtered signal with a high correlation to the original one. The processing time is the current limitation of CUDR due to the two-time implementation of UDR, while some internal steps have yet to be optimized. In our future work, some image processing methods will be investigated to undertake the tasks in the cascaded stage of CUDR for processing time enhancement.

VI. Conclusion

An enhanced smoothing algorithm using the Upscale and Downscale Representation idea combined with the cascaded concept is introduced in this work where the output of the first UDR is the input of the second one. CUDR significantly enhances the signal smoothing result compared to UDR and other comparative time-domain filters, especially at low level of *SNR*. The obtained results have confirmed the potential of vision-based methods in EEG-like signals, the effectiveness of which in real-EEG signal will be verified in our future work.

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