A Comprehensive Assessment of the Performance of Modern Algorithms for Enhancement of Digital Volume Pulse Signals

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***Abstract*—Digital volume pulse(DVP) refers to the physiological signal that quantifies the changes in blood volume in the artery during breathing. DVP signals are acquired using methods such as invasive catheterization, mechanical tonometry and photoplethysmography. From the DVP signals critical biological parameters such as heart rate, stiffness index, reflectivity index and pulse wave velocity can be computed. These parameters have shown promise in detecting the early onset of cardiovascular disease (CVD). Thus it is critical that these parameters should be estimated with utmost precision. However DVP signals are corrupted with artifacts due to improper mounting of the sensor, power line interference and other random noises in environment. These artifacts would lead to incorrect estimation of the aforementioned parameters. In this paper the authors evaluate the performance of state of the art algorithms for denoising DVP signals. Denoising using wavelet transforms, empirical mode decomposition, adaptive filters, morphological filters, anisotropic diffusion, total variation denoising and non local means algorithm has been considered in our work. Metrics: mean squared error(MSE), mean absolute error(MAE), signal to noise ratio(SNR), peak signal to noise ratio (PSNR), cross correlation and central processing unit(CPU) consumption time have been computed to assess the performance of each of the methods. From our study, it is concluded that multivariate wavelet denoising yields the best performance and is hence the most suitable method for enhancement of DVP signals.**

***Index Terms*—Digital volume pulse (DVP), Denoising, Wavelet transform, Multivariate wavelet denoising, Empirical mode decomposition (EMD), White gaussian noise (WGN)**

I. Introduction

The digital volume pulse signal (DVP) is a measure of the fluctuation of blood volume in the artery during breathing. The DVP can be acquired both invasively and non-invasively. Till about a few decades ago, invasive catheterization was used for measuring the changes in blood volume [1]. Recent methods for non-invasive measurement of DVP signals include Photoplethysmopgraphy [2], tonometry [3] and use of force sensing resistors [4]. Physiological parameters namely stiffness index and pulse wave velocity, computed using the DVP are critical markers for detecting early onset of cardiovascular disease (CVD) [5]. Thus it is essential that these parameters are estimated correctly. However like any other biomedical signals, DVP signals are prone to artifacts due to improper mounting of sensors, subject movement, power line interference and other random noises. Thus, the acquired DVP signals must be accurately denoised.

In our work, denoising using wavelet transforms: wavelet-thresholding, multivariate wavelet denoising (wavelet-PCA), empirical mode decomposition-detrended fluctuation analysis (EMD-DFA), adaptive filters : NLMS and RLS filters, morphological filters, anisotropic diffusion, total variation denoising and non local means algorithm has been explored. The white gaussian noise model is commonly used in information theory to mimic the effect of random processes. WGN also closely emulates the type of noise present in real world biomedical signals [6]. In our method, noiseless or clean DVP signals are corrupted with SNR= 30 db white gaussian noise (WGN). The signals are then denoised one by one using each of the aforementioned techniques. In our work a Monte-Carlo based approach has been used to tune the filter parameters to achieve optimal denoising. The stopping criterion for the denoising was selected based on the parameter set that yielded the minimum mean squared error. A few methods for denoising DVP signal have been proposed in previous works Yang et.al (2013) [7], Zhao *et al*. (2013) [8]. However an in depth analysis into the performance of other methods has not been carried out in previous literature. The aim of the authors is to carry out a comprehensive analysis to identify the most suitable algorithm for denoising these signals.

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Standard metrics: mean squared error (MSE), mean absolute error (MAE), signal to noise ratio (SNR), peak signal to noise ratio (PSNR), cross correlation (xcorr) and CPU consumption were computed to evaluate the performance of the each of these methods. The block diagram in Fig. 1 summarizes the procedure followed in this paper.

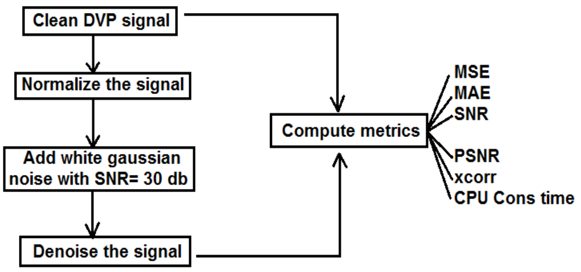

Figure 1. Block diagram of the procedure followed in this paper

II. Dataset

The dataset used in this paper has been acquired from the works of Sundar & Venkat (2015) [9]. A total of 20 clean DVP signals have been used in this paper. 10 signals were recorded using photoplethysmography and 10 were acquired using force sensing resistors placed over the radial artery. We use these signals as our ground truth signals in evaluating the performance of denoising algorithms. The subjects were asked to remain completely still during the study to avoid motion artifacts and measurements were made as noise free as possible. The signal data comprised of the recordings of 6 male and 4 female subjects, between the ages of 21-68. The signals were acquired digitally using a NI MyDAQ at a sampling rate of 500 Hz and digitized to a 16 bit resolution. Fig. 2 shows a sample clean DVP signal acquired using PPG.

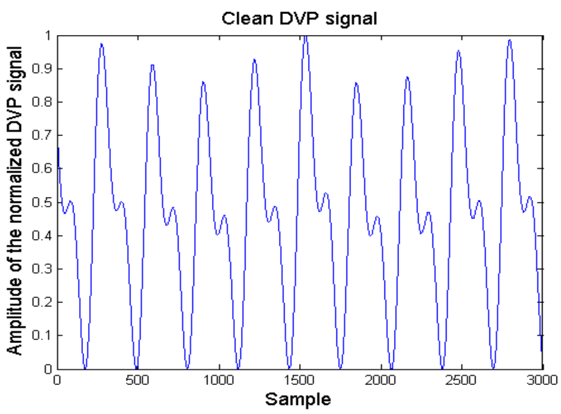

Figure 2. A sample normalized, clean DVP signal

III. Denoising Algorithms

A. *Wavelet-Thresholding*

Since its advent, wavelet transforms have found great applications in denoising signals [10]. Wavelet transforms with hard, soft and universal thresholding methods have shown good performance in denoising biomedical signals in previous literature. The authors hence explore the use of this technique for denoising DVP signals. In wavelet- thresholding, the noisy signal is first decomposed into its detail and approximation coefficients using wavelet decomposition. A denoising threshold is then computed using certain techniques. Some popular threshold estimation techniques include : stein's unbiased risk estimate, penalized medium threshold, square root log threshold, minimax etc.ss The coefficients are then thresholded using this value. The denoised signal is obtained by wavelet based reconstruction of the thresholded coefficients. After several experiments with different thresholding techniques and threshold selection methods, the authors have found that the bi-orthogonal 3.3 wavelet (bior3.3) with 6 levels of decomposition and penalized medium threshold, and hard thresholding yields the best denoising. The value of tuning parameter alpha is set equal to 2 and standard deviation of the zero mean Gaussian white noise is set equal to that of the 3rd detail coefficient. Fig. 3 shows a noisy DVP signal with additive white Gaussian noise of SNR= 30 db and its denoised version obtained after denoising using wavelet-hard thresholding with the aforementioned parameters.

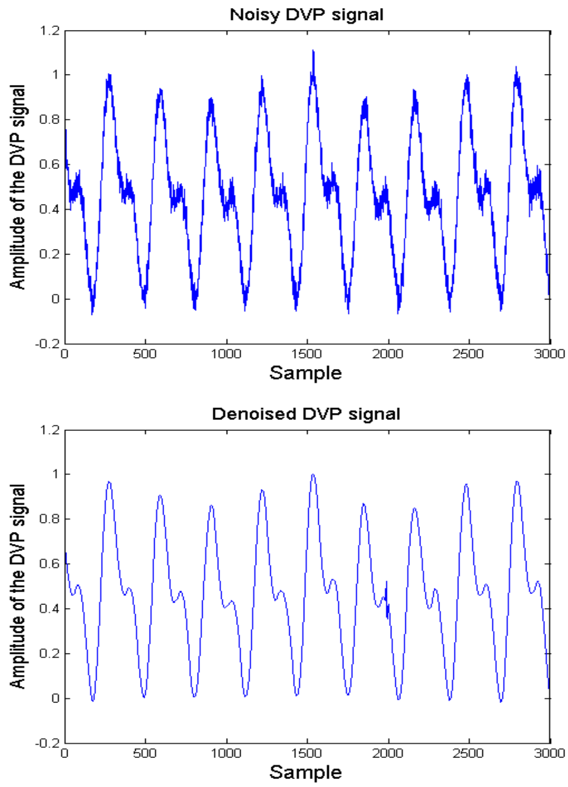

Figure 3. Noisy DVP signal and denoised signal obtained using wavelet- hard thresholding

B. *Multivariate Wavelet Denoising (Wavelet-PCA)*

Multivariate wavelet denoising is a noise removal algorithm, proposed by Aminghafari et.al (2006) [11], that combines univariate wavelet denoising with principal component analysis. This technique incorporates univariate wavelet decomposition, in the basis where the estimated noise co-variance matrix is diagonal to non-centered PCA approximations in the wavelet domain. This method has show promising results in denoising ECG signals in previous works and is hence explored in our application [12]. The authors have found that a 5 level wavelet decomposition with a 5th order Coiflet wavelet yields the best results. The Kaiser's rule or the heuristic rule has been used to select the number of principal components to be retained. Fig. 4 shows the denoised signal obtained using multivariate wavelet denoising. The waveform in Fig. 4 closely resembles the clean DVP waveform in Fig. 2. Hence multivariate wavelet denoising yields a good performance.

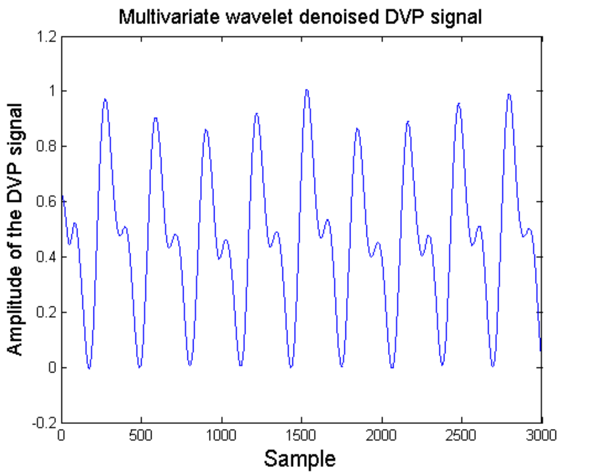

Figure 4. Denoised signal obtained on multivariate wavelet denoising

C. *Denoising Using Empirical Mode Decomposition-Detrended Fluctuation Analysis (EMD-DFA)*

Empirical mode decomposition (EMD) is Huang's data driven decomposition tool [13]. EMD sifts the signal into components called IMFs or intrinsic mode functions and the trend called the residue. By summing the decomposed IMFs the original signal can be retrieved again. In this work the authors use a cubic spline interpolant to estimate the maxima and minima envelopes of the signal. The two threshold stopping proposed by Rilling et.al (2003) [14] has been used in our work. In this method, two threshold values are chosen to ensure globally small fluctuations in the mean, while simultaneously taking into account locally large excursions. The values of 0.05 and 0.5 have been chosen as threshold values in our work. Detrended fluctuation analysis is a method used for measuring the self-affinity of a signal [15]. Using DFA the fractal scaling index (α) is computed. The value of α is an estimate of the fractal-like autocorrelation of the signal. If the value of α ≤ 0.5 then the time series is likely to be uncorrelated or just noise. Empirical mode decomposition-detrended fluctuation analysis, proposed by Mert & Akan (2014) has shown promising results in denoising common biomedical signals and is hence explored in our work.

The procedure followed in EMD-DFA denoising is as listed below:

1) Decompose the signal into 'N' IMFs using empirical mode decomposition
2) Perform detrended fluctuation analysis on each of the IMFs and compute the α value.
3) If the value of α ≤ 0.5, then discard that IMF
4) Reconstruct the signal using the leftover IMFs to obtain the denoised signal

Fig. 5 shows the IMFs obtained on decomposing the signal in Fig. 2 using EMD. For the sample DVP signal shown in Fig. 2, the values of α for each of 7 IMFs are 0.4340, 0.3121, 0.3510, 0.3923, 0.6275, 0.7821 and 0.9791. Thus values of α for IMFs 1,2,3 and 4 are less than 0.5 . Thus these IMFs are considered as noise and discarded while reconstructing the signal. Fig. 6 shows the denoised signal obtained using EMD-DFA.

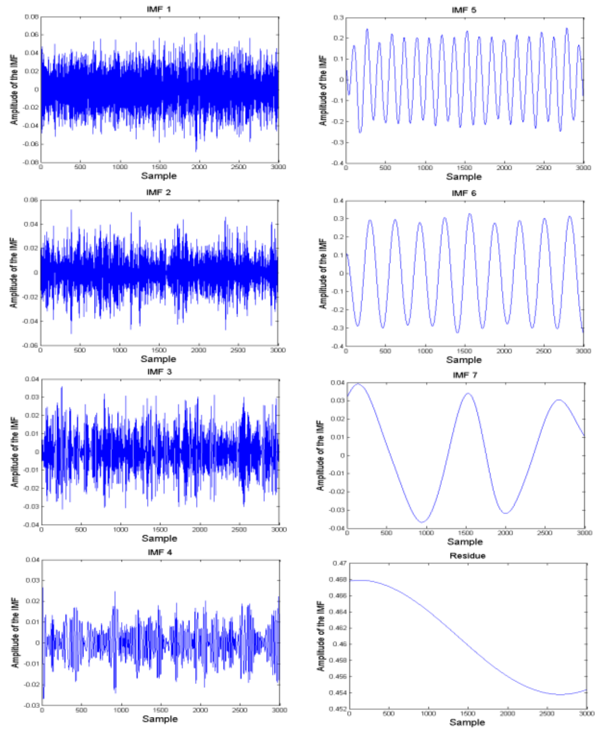

Figure 5. IMFs and residue obtained on decomposing the sample DVP signal in figure

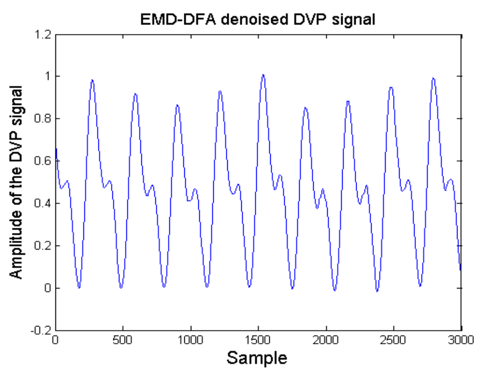

Figure 6. Denoised signal obtained using empirical mode decomposition-detrended fluctuation analysis

D. Adaptive filtering: NLMS and RLS Filters

Adaptive filtering is a technique of iteratively modeling the relationship between filter inputs and outputs subject to certain conditions. The advantage of the adaptive filter over conventional filters is that it automatically tunes its coefficients to filter new inputs [16]. Since its advent a few decades ago, adaptive filters have been used extensively in signal denoising applications. In this work the authors have evaluated the performance of the NLMS (normalized least mean squares filter) and the RLS (recursive least squares filter) filters. For NLMS filtering, a 10^{th} order FIR filter with a value frequency constraint scalar of 0.01 is used. The value of NLMS step size is set to 1 and the value NLMS offset was set to 40. The number of taps of the filter was set equal to 11. The NLMS leakage factor is set equal to 1. For RLS filtering a 10^{th} order FIR filter with a value frequency constraint scalar of 0.01 has been used. The value of forgetting factor was set to 0.98. The initial inverse covariance matrix was set equal to a 10 multiplied by a 11 x 11 identity matrix. Fig. 7 shows the sample denoised signal obtained on denoising using NLMS filtering.

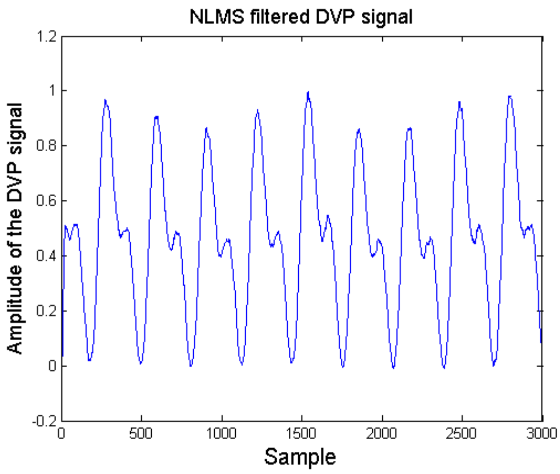

Figure 7. Denoised signal obtained using NLMS filtering

From visual inspection it observed that adaptive filters yield a relatively poor performance and there is still noise visible in the signal. A structural glitch is also observed in the beginning which would lead to poor cross correlation.

E. Morphological Filtering

Morphological filtering involves a set of non-linear operations, performed on a signal with respect to an image, termed as the structuring element [17]. Top hat transform is a morphological filtering method used to extract small details in an image or signal. Works by Zhongguo et.al [18] suggest that morphological filters show promise in denoising ECG signals. The use of the same is hence explored in our study. Works by Bhateja et.al (2013) [19] propose that the use of a structuring element such as the one shown in Fig. 8 can be used to estimate the noise in the signal. This estimated noise can then be removed from the signal. Fig. 9 shows the 'morphologically estimated' noise present in the noisy signal shown in Fig. 3. Fig. 10 shows the denoised DVP, obtained using morphological filtering.

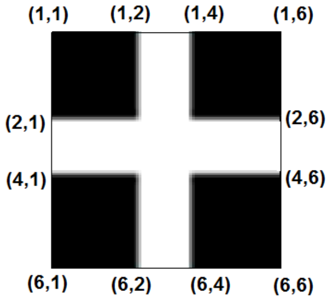

Figure 8. Structuring element used for top-hat filtering

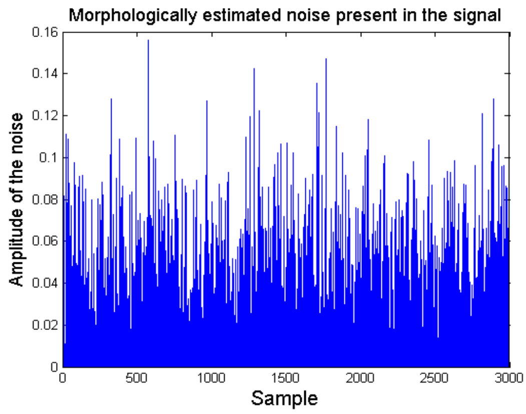

Figure 9. Morphologically estimated noise present in the signal

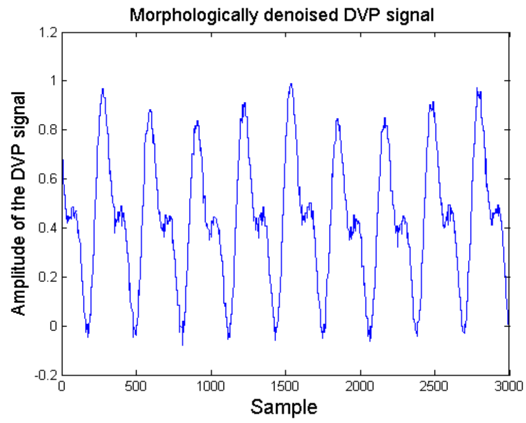

Figure 10. Morphologically denoised signal

From visual inspection, it can be observed the morphological filtering performs poorly, as there is still noise retained in the DVP signal. Morphological filtering would also be relatively computationally complex as it involves an additional step of creation of the structuring element (SE).

F. Anisotropic Diffusion

Anisotropic diffusion, proposed by Perona & Malik (1990) [20] is a popular as an image denoising algorithm. This algorithm works based on a method similar to creation of a scale space, wherein the signal or image iteratively generates a family of several blurred images or signals using the diffusion process. Although used extensively for image denoising, this validity of this method in removal of noise from signals has not been explored extensively. Here the authors explore the use of this method for denoising DVP signals. In denoising, the number of iterations was set equal to 100. The value of integration constant Δ is set equal to 0.25. The value of gradient modulus threshold κ, used to control the conduction is set to 30 and the value of conduction coefficient is chosen such that it privileges wide regions of the signal over smaller ones. Fig. 11 shows the denoised signal obtained using anisotropic diffusion.

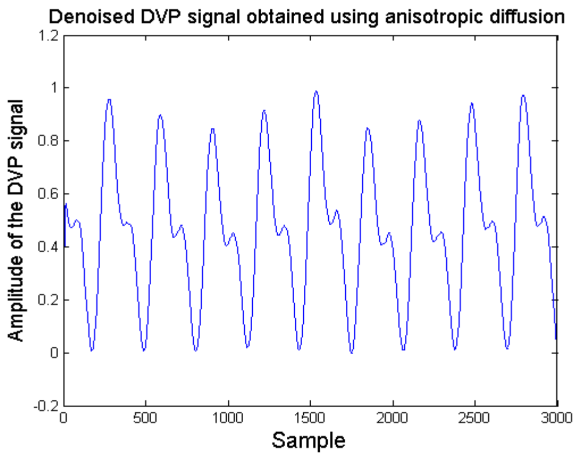

Figure 11. Denoised signal obtained using anisotropic diffusion

G. Total Variation Denoising

Total variation denoising (TVD) proposed by Rudlin et.al (1992) [21] is primarily a noise removal algorithm. Total variation (TV) is a mathematical function that identifies marginally different parameters related to codomain measure. Let f(t) represent a continuous function defined on a certain interval t= [t1 t2]. Total variation can be defined as a measure of the 1-D arc length of the curve with paramedic equation f(t), for t∈ [t1 t2].This algorithm relies on the principle that noisy signals have a higher total variation in comparison to normal signals. Andrei et.al (2011) [22] propose that total variation denoising shows promise in the removal of noise from ECG signals. The authors hence explore the use of this algorithm in removal of noise from DVP signals. In our work, the value of regularization parameter was set equal to 0.03 and the number of iterations was set to 100. Fig. 11 shows the denoised signal obtained after total variation denoising.

From Fig. 12, it is observed that DVP yields a poor performance, as both structural integrity of the signal is lost and the noise is not completely removed.

H. Denoising Using Non Local Means Algorithm

Non local means proposed by Buades et.al (2005) [23] is a popular image denoising algorithm. The non local means filter removes noise from the signal by computing the mean of the data points in the time series, weighted by their similarity to a certain target data point. Works by Tracey & Miller (2012) [24] show that this algorithm yields a better performance in denoising ECG signals in comparison to previous methods. The use of this algorithm in removal of noise from DVP signals is hence explored. For denoising the value of patch half width, or the smallest size of feature, in samples is set equal to 10. The neighbour hood search width has been set equal to 20, and the value of gaussian scale factor or ϰ is set as 10. Fig. 13 shows the denoised signal obtained using non local means algorithm.

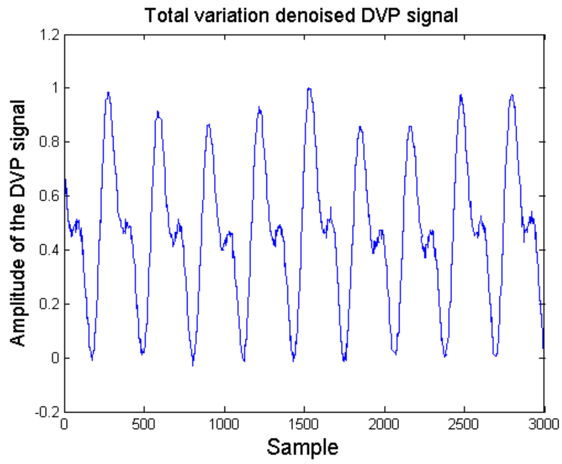

Figure 12. Total variation denoised DVP signal

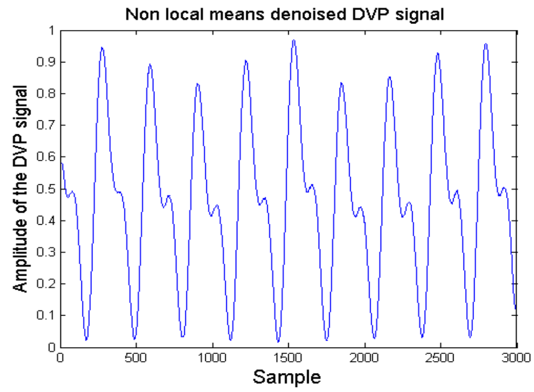

Figure 13. Denoised signal obtained using non local means denoising

IV. Evaluating the Performance of Denoising Algorithms

To evaluate the performance of the aforementioned algorithms, metrics: MSE, MAE, SNR, PSNR, cross correlation and CPU consumption time have been computed. These metrics have been chosen keeping in mind that denoising algorithms should not only be accurate but also be fast so that appropriate real time diagnosis can be performed using the signals. Each of metrics are briefly explained below.

A. Mean Squared Error (MSE)

MSE is a metric that is used to evaluate the accuracy of denoising. The lower the value of MSE, the closer is the denoised signal to the original, hence better denoising. Let x(n) represent the clean DVP signal , x'(n) represent the denoised signal and N represent the length of the signal. Let 'n' represent the sample number, where n=1,2,3..N. MSE can be defined as :

$$\text{MSE} = \frac{\sum_{n=1}^{N}\left(x(n)-x\prime(n)\right)^2}{N} \qquad (1)$$

A small value of MSE indicates that the denoised signal is similar to the original signal and is hence accurately denoised.

B. Mean absolute error (MAE)

MAE is a metric similar to MSE is used to evaluate the accuracy of denoising. The lower the value of MAE, the better is the denoising. Using the aforementioned symbols, MAE is defined as:

$$\text{MAE} = \frac{\sum_{n=1}^{N}|\left(x(n)-x\prime(n)\right)|}{N} \qquad (2)$$

C. Signal to Noise Ratio (SNR)

SNR is a common metric used to assess the performance denoising methods. SNR is inversely proportional to log(MSE). SNR can defined as :

$$\text{SNR} = 10\log_{10}\frac{\sum_{n=1}^{N}x(n)^2}{\sum_{n=1}^{N}(x(n)-x\prime(n))^2} \qquad (3)$$

A high value of SNR indicates good denoising.

D. Peak Signal to Noise Ratio (PSNR)

PSNR is a metric similar to SNR. Similar to SNR, the hgiher the value of PSNR, the more accurate is the denoising. PSNR can be defined as:

$$\text{PSNR} = 20\log_{10}\frac{max(x(n))}{RMSE} \qquad (4)$$

where RMSE is the square root of MSE.

E. Cross Correlation (xcorr)

Cross correlation measure the similarity between two discrete time sequences.. If the value of cross correlation xcorr is close to 1, then the denoised signal and the noisy signal closely resemble each other. Using the aforementioned symbol convention, cross correlation can be defined as:

$$xcorr = \frac{E\left((x'(n)-\mu_{x'})(x(n)-\mu_x)\right)}{\sigma_{x\prime}\,\sigma_x} \qquad (5)$$

where $\mu_{x'}$ and μ_x represent the average values of the signal x'(n) and x(n) respectively and $\sigma_{x'}$ and σ_d denote the respective standard deviations of the two signals. The operator E() is the statistical expectation or mean function.

A computer with an Intel core i7 processor operating at 2 GHz with 6 GB RAM has been used to perform all computations. The next section evaluates the performance of the aforementioned techniques using these metrics.

TABLE I. AVERAGE VALUE OF METRICS OBTAINED FOR THE 20 DVP SIGNALS

Denoising method	MSE	MAE	SNR	PSNR	xcorr	CPU consumption time (seconds)
Wavelet soft thresholding	0.000122	0.008542	33.685010	39.124709	0.999168	0.415362
Wavelet-PCA	0.000041	0.004398	38.416612	43.856311	0.999721	0.301009
EMD-DFA	0.000074	0.006952	35.879405	41.319104	0.999498	0.542145
NLMS filter	0.003176	0.035488	19.541285	24.980984	0.978306	0.385465
RLS filter	0.002247	0.032830	21.043983	26.483682	0.984562	0.428116
Morphological filters	0.000957	0.025796	24.750665	30.190364	0.997371	1.743406
Anisotropic diffusion	0.000577	0.008615	26.950698	32.390397	0.996153	0.647014
Total variation denoising	0.000243	0.012320	30.696227	36.135926	0.998332	0.256200
Non local means	0.000328	0.015170	29.402974	34.835955	0.999086	0.275484

F. Comparison of the Performance of Different Methods

The value of the aforementioned metrics has been computed for each of the 20 signals. The average of these metrics for each of the 20 signals is then computed. Table I shows the average value of metrics obtained after averaging. From Table I, it is observed that multivariate wavelet denoising or wavelet-PCA yields the best results in terms of accuracy of denoising, as it yields the lowest value of MSE, MAE and highest values of SNR, PSNR and cross correlation. This method also yields a nominal CPU consumption of 0.3 seconds per signals, which is sufficient for real world applications. As noted earlier, adaptive filters show a poor performance in denoising. Morphological filters also show a poor performance both in terms of speed and accuracy. Total variation denoising yields the fastest response but relative poor denoising. Other methods yield relatively good performances in terms of speed and accuracy, but marginally fall short of wavelet-PCA. These results also agree with the prior qualitative performance assessment carried out using visual inspection. Fig. 14 shows the plots of SNR for each of the 20 signals used in our work denoised using different methods. It can be observed from the plot below that wavelet PCA yields the highest value of SNR for each of the 20 signals and is clearly superior to other methods.

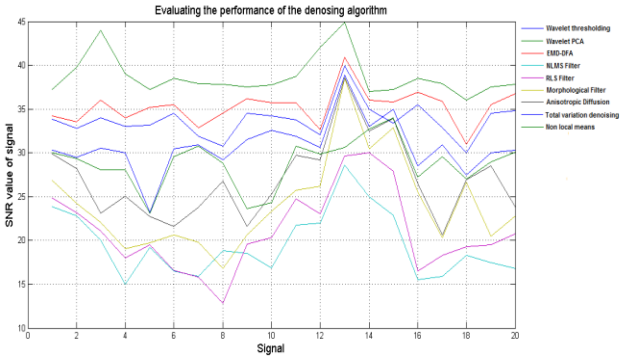

Figure 14. SNR versus signal for each of the different methods.

V. Conclusion

In this paper, the authors evaluate the performance of state of the art algorithms in denoising digital volume pulse signals. Denoising using wavelet transforms, empirical mode decomposition, adaptive filters, morphological filters, anisotropic diffusion, total variation denoising and non local means algorithm has been explored in our study. Standard metrics were used to assess both the speed and accuracy of denoising. From our study it is concluded that multivariate wavelet denoising or wavelet-PCA yields the best denoising and is hence the most suitable for real world DVP enhancement applications.

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