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Additive and exclusive noise suppression by iterative trimmed and truncated mean algorithm

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ABSTRACT

An iterative trimmed and truncated arithmetic mean (ITTM) algorithm is proposed, and the ITTM filters are developed. Here, trimming a sample means removing it and truncating a sample is to replace its value by a threshold. Simultaneously trimming and truncating enable the proposed filters to attenuate the mixed additive and exclusive noise in an effective way. The proposed trimming and truncating rules ensure that the output of the ITTM filter converges to the median. It offers an efficient method to estimate the median without time-consuming data sorting. Theoretical analysis shows that the ITTM filter of size n has a linear computational complexity $\mathcal{O}(n)$. Compared to the median filter and the iterative truncated arithmetic mean (ITM) filter, the proposed ITTM filter suppresses noise more effectively in some cases and has lower computational complexity. Experiments on synthetic data and real images verify the filter's properties.
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1. Introduction

Noise suppression has drawn great attention and is used in a broad range of applications, such as imaging, communications, geology, hydrology and economics [1]. A noise corrupted signal can be modeled as

$$x_i = \begin{cases} s_i + v_i & \text{with probability } p \\ e_i & \text{with probability } (1-p), \end{cases} \tag{1}$$

where s_i, v_i and e_i denote the noise free signal, the additive and exclusive noise, respectively. The occurrence probability of the two types of noise is controlled by p, $p \in [0, 1]$. The additive noise v_i is in general symmetrically distributed with zero mean. It could be short- or long-tailed noise, such as Gaussian or Laplacian noise. The exclusive noise e_i could be impulsive noise with uniform distribution, or pepper & salt noise. Great effort has been devoted to developing the noise suppression filters based on the noise model.

Many filters were designed to attenuate the additive noise that corresponds to $p=1$. The most frequently occurring noise in practice is the additive Gaussian noise, and the optimal filter in suppressing it is the mean filter. Its simplicity in realization and the availability of rigorous mathematical tool lead to the rich class of the linear finite impulse response (FIR) filters. The linear FIR filters are effective in attenuating the additive Gaussian noise but not the long-tailed noise. This results in the development of the nonlinear filters. The median filter [1], which is the most widely used one among the nonlinear filters, provides a powerful tool for signal processing. It has good properties in long-tailed noise suppression and structure preservation. However, it destructs fine signal details and cannot effectively suppress the additive Gaussian and other short-tailed noise. This leads to the various extensions of the median filter, including the weighted median filters [1], the weighted rank order Laplacian of Gaussian filter [2,3], the steerable weighted median filter [4], the fuzzy rank filters [5], the truncation filters [6] and various adaptive noise switching median filters [7–10]. The merits

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of the mean and median filters lead to another branch of filters which make compromises between these two filters, such as the mean–median (MEM) filter [11] and the median affine (MA) filter [12]. The output of these filters varies smoothly between the mean and median by adjusting some free parameters. Selecting the optimal parameters to make them adaptive to signal types is not an easy task though some efforts were made [12].

Both the additive and exclusive noise exist if p in (1) is smaller than 1. As the exclusive noise completely replaces the original samples, the most effective way is to trim (remove) such samples and use the exclusive-noise-free ones in a local region to restore the signal. The median filter is optimal in suppressing the exclusive noise by trimming all the samples except the middle one. The filters to suppress the mixed additive and exclusive noise include the α-trimmed mean (αT) filter [13], the modified trimmed mean (MTM) filter [14] and the switching bilateral filter (SBF) [15]. The αT filter discards some samples strictly relying on their rank. This may not be effective as it does not consider the dispersion of the data [12]. The MTM filter is sensitive to the small variation of samples located close to the threshold [12]. The SBF separates the impulsive noise from the Gaussian noise [15] and suppresses these two types of noise respectively. Its performance drops in dealing with the long-tailed noise. In addition, all these filters require both data sorting and arithmetic computing. Compared to the arithmetic computing, the data sorting is much more time-consuming [16].

Nonlinear filters without data sorting were desirable and proposed in [17–19]. The iterative truncated arithmetic mean (ITM) filter [17] iteratively truncates the extreme samples to a dynamic threshold that ensures the filter's output converges to the median. The stopping criterion of the ITM filter makes it own merits of both the arithmetic mean and order statistic median operations in attenuating the short- and long-tailed noise. By truncating the extreme samples, the ITM1 filter outperforms both the mean and median filters in suppressing Laplacian noise and the Gaussian–Laplacian mixed noise [17]. By discarding all the truncated samples and using the mean of the remaining ones as the output, the ITM2 filter surpasses other filters in attenuating the impulsive-contaminated Gaussian noise [17]. A realization of the ITM filter [18] is verified to perform faster than the standard median filter. The ITM filter is extended to the weighted ITM filter to realize the band- and high-pass filters [19]. However, keeping all the truncated samples (ITM1) or trimming all the truncated samples (ITM2) may not be optimal if both the additive and exclusive noise exist. Moreover, further analysis in this paper reveals that the truncation threshold is largely affected by the extreme samples even if they are truncated. This reduces the convergence of the truncation threshold, and therefore leads to a high computational complexity.

In this paper, we propose a trimmed and truncated arithmetic mean (ITTM) algorithm to alleviate the above problems. The proposed algorithm iteratively trims and truncates the extreme samples simultaneously. Without sorting, the extreme samples are symmetrically trimmed from the input data set, and the remaining ones are truncated to a dynamic threshold. Three types of filter outputs are developed on the basis of the ITTM algorithm. The proposed trimming and truncating rules guarantee the filters' outputs approaching the median by increasing the number of iterations. With the stopping criterion given in [17] to terminate the iteration, the proposed ITTM filter is not only faster than the ITM filter, but also more effective in attenuating some types of noise.

2. The proposed ITTM filter

We propose the iterative trimmed and truncated arithmetic mean (ITTM) filters based on analysis of the ITM filter.

2.1. Iterative truncated arithmetic mean filter

As distinct from the mean filter that averages all samples and the median filter that chooses one sample as the output, the iterative truncated arithmetic mean (ITM) filter [17] iteratively truncates the extreme samples and uses the truncated mean as the filter output. Starting from $\mathbf{x}=\mathbf{x}_0$, it truncates samples in $\mathbf{x}$ to a dynamic threshold as shown by Algorithm 1.

Algorithm 1. Truncation procedure of the ITM algorithm.

Input: $\mathbf{x}_0 \Rightarrow \mathbf{x}$; **Output**: Truncated $\mathbf{x}$;
do
1) Compute the sample mean : $\mu=\text{mean}(\mathbf{x})$;
2) Compute the dynamic threshold : $\tau=\text{mean}(|\mathbf{x}-\mu|)$;
3) $b_l=\mu-\tau,\ b_u=\mu+\tau,$ and truncate $\mathbf{x}$ by :

$$x_i=\begin{cases} b_u & \text{if } x_i>b_u \\ b_l & \text{if } x_i<b_l \\ x_i & \text{otherwise;}\end{cases}$$

while *the stopping criterion S is violated*;

The ITM filter has two types of outputs [17]. The type I output ITM1 is

$$y_{t1}=\text{mean}(\mathbf{x}). \tag{2}$$

Let $\mathbf{x}_r=\{x_i|b_l<x_i<b_u\}$ and n_r be the number of samples in $\mathbf{x}_r$. The type II output ITM2 is

$$y_{t2}=\begin{cases}\text{mean}(\mathbf{x}_r) & \text{if } n_r>\xi \\ \text{mean}(\mathbf{x}) & \text{otherwise.}\end{cases} \tag{3}$$

The parameter ξ is used to avoid an unreliable mean in case that too few samples remain in $\mathbf{x}_r$. It is set to $\xi=n/4$ in [17].

2.2. The proposed ITTM filters

Keeping all the truncated samples makes the ITM1 filter less effective in suppressing the exclusive noise. Trimming all the truncated samples causes the ITM2 filter not optimal in dealing with the additive noise. Neither the ITM1 nor ITM2 filters can effectively deal with the case that both the additive and exclusive noise exist. In addition, a large number of iterations may be in demand for the ITM algorithm to converge as its truncation threshold, which is the mean absolute deviation (MAD) of the

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