FIR-Median Hybrid Filters

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Abstract—**This paper introduces a new generalized class of median-type filters which we call FIR-median hybrid (FMH) filters. The input signal $x(n)$ is filtered with M linear phase FIR filters, and the output of the FMH filter is the median of the outputs of the FIR filters. The statistical properties of the FMH filters are analyzed for input signals with Gaussian, double exponential, and uniform density functions. It is shown that FMH filters have essentially the same statistical properties and same type of root signals as the standard median (SM) filters. FMH filters preserve corner points and ramps and attenuate impulsive-type noise components effectively. An interesting subclass of the FMH filters requiring only one scaling multiplier, two additions, and three compare/swap operations irrespective of the filter length is introduced. In the examples, speed improvement by a factor of 450 is obtained over an otherwise approximately equivalent SM filter.**

I. Introduction

MEDIAN filtering is a nonlinear filtering technique which is known for preserving sharp changes in signals and for being particularly effective in removing impulsive noise. For signal processing, the median operation was first suggested by Tukey [1], [2]. Standard median (SM) filters have found applications in one- and two-dimensional signal processing, and many authors have analyzed the statistical and root signal properties of these filters [3]–[6].

The standard median filter algorithm is a simple operation of choosing the median value of the samples inside a moving window of fixed length. Let S_N be a set of N samples $\{x_1, x_2, \cdots, x_i, \cdots, x_N\}$ where $N = 2k + 1$. The median is denoted by $y = \text{MED}[x_i \mid x_i \in S_N]$. By the definition, the median y is both the $(k+1)$st largest and the $(k+1)$st smallest element in S_N. In principle, the implementation of an SM filter requires a simple nonlinear operation. However, when the number of the samples is large, the ordering procedure becomes cumbersome.

In this paper, we introduce and analyze a new class of median-type filters which contain FIR substructures. These filters, called FIR-median hybrid (FMH) filters, greatly alleviate the data sorting problem since median is taken over the outputs of the FIR substructures and the number of the substructures is much smaller than the number of the data samples inside the filter window [7].

In Section II, we describe the basic FMH filter structures. The root structures of the filters are analyzed in Section III and the noise attenuation properties in Section IV. In Section V, we compare the responses of the FMH and SM filters to noisy edges. The implementation of the filters is described in Section VI, and practical examples showing the efficiency of the FMH filters are given in Section VII.

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II. FIR-Median Hybrid Filters

In FMH filters, the input signal $x(n)$ is filtered with M linear phase FIR filters $H_j(z), j = 1, \cdots, M$. The output of the FMH filter is $y(n) = \text{MED}[y_1(n), y_2(n), \cdots, y_M(n)]$ where $y_1(n), \cdots, y_M(n)$ are the outputs of the FIR filters $H_j(z)$ (see Fig. 1).

The properties and the number of the subfilters $H_j(z)$ depend on the application. In this paper, we will focus our attention on the simple cases where $M = 3$ or $M = 5$ and the substructures are simple averaging filters with different lengths. We will further restrict our attention to those FMH filters where the tap coefficients h_{ij} in Fig. 1 do not overlap, as this will give desirable root signal properties and simplify the statistical analysis of noise attenuation.

In the case $M = 3$, we analyze the FMH filters with the following averaging subfilters:

$$H_1(z) = \frac{1}{k}[z^k + z^{k-1} + , \cdots , + z^1]$$

$$H_2(z) = 1$$

$$H_3(z) = \frac{1}{k}[z^{-1} + z^{-2} + , \cdots , + z^{-k}]. \quad (1)$$

In (1), the time reference is, for convenience, taken to the center of the filter of Fig. 1.

With $M = 5$, we treat the cases where the length of the second and fourth filters may be 1 or $\lfloor (N-1)/4 \rfloor$, and the length of the first and fifth filters then becomes $(N-3)/2$ or $\lceil (N-1)/4 \rceil$, respectively. The subfilters in the case $M = 5$ are thus

$$H_1(z) = \frac{1}{k-1}[z^k + z^{k-1} + , \cdots , + z^2]$$

$$H_2(z) = z^1$$

$$H_3(z) = 1$$

$$H_4(z) = z^{-1}$$

$$H_5(z) = \frac{1}{k-1}[z^{-2} + z^{-3} + , \cdots , + z^{-k}] \quad (2)$$

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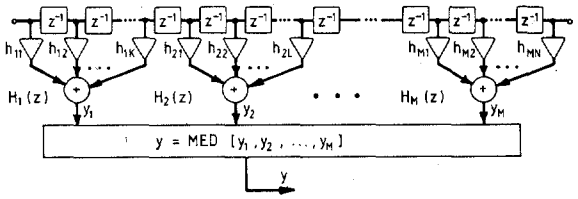


Fig. 1. General structure of the FIR-median hybrid (FMH) filters.

or

$$H_1(z) = \frac{1}{\lceil k/2 \rceil}\left[z^k + z^{k-1} + , \cdots , + z^{\lfloor k/2 \rfloor + 1}\right]$$

$$H_2(z) = \frac{1}{\lfloor k/2 \rfloor}\left[z^{\lfloor k/2 \rfloor} + z^{\lfloor k/2 \rfloor - 1} + , \cdots , + z^1\right]$$

$$H_3(z) = 1$$

$$H_4(z) = \frac{1}{\lfloor k/2 \rfloor}\left[z^{-1} + z^{-2} + , \cdots , + z^{-\lfloor k/2 \rfloor}\right]$$

$$H_5(z) = \frac{1}{\lceil k/2 \rceil}\left[z^{-\lfloor k/2 \rfloor - 1} + z^{-\lfloor k/2 \rfloor - 2} + , \cdots , + z^{-k}\right], \quad (3)$$

where $\lfloor k/2 \rfloor$ is the largest integer less than or equal to $k/2$, and $\lceil k/2 \rceil$ is the least integer equal to or higher than $k/2$.

In all these cases, the length of the central subfilter is one to guarantee that the sharp edges of the signal are not distorted. The above filter types are computationally efficient and have essentially the same types of root signals as the SM filter.

III. Root Signals

The convergence of the signal into a root, which is not affected by further filterings, is an important property of the median-type filters [5]. Root signals and noise attenuation together constitute a very useful characterization of median-type filters. The definitions used in the analysis of the root signals of the SM, and also the FMH filters with total window length $N = 2k + 1$, are as follows.

1) A *constant neighborhood* is at least L_R consecutive identical valued points such that the constant neighborhoods and a joining edge together are monotone.

2) An *edge* is a monotone region between two constant neighborhoods of different values. The connecting monotonic region cannot contain any constant neighborhood.

3) An *impulse* is a constant neighborhood followed by at least one, but not more than $L_R - 1$ points, which are then followed by another constant neighborhood having the same value as the first constant neighborhood. The two boundary points of these at most $L_R - 1$ points do not have the same value as the two constant neighborhoods.

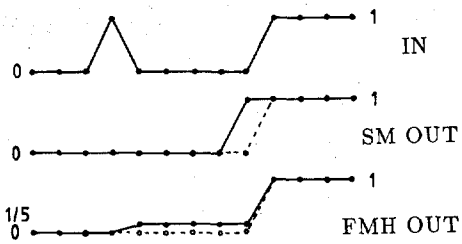


Fig. 2. Outputs of the SM filter and the FMH filter of (1) when there is an impulse near the edge and $k = 5$ in both filters. The dotted lines show the outputs without the impulse in the input signal.

4) An *oscillation* is a sequence of points which is not part of a constant neighborhood, an edge, or an impulse.

A necessary and sufficient condition for a finite length signal to be a root signal of the SM filter is that the signal consists only of constant neighborhoods and edges with $L_R = k + 1$ [5]. It is easy to show that a sufficient, but not a necessary, condition for a signal to be a root signal of the FMH filter is also that it consists only of constant neighborhoods and edges. The critical length L_R is $2k$ for the FMH filter of (1), $k + 1$ for the FMH filter of (2), and $k + \lfloor k/2 \rfloor$ for the FMH filter of (3), respectively. In each case, the total window length of the filter is $N = 2k + 1$.

In the SM filter, if an impulse and an edge are into the same direction from the prevailing constant neighborhood and the distance between them is $k + 1$ or less, the impulse causes jitter into the position of the edge. The jitter is equal to the length of the impulse and does not depend on k as long as the whole impulse and the edge are inside of the filter window. In the FMH filter of (1), the position of the impulse remains the same, its height may change but it does not cause edge jitter. The level of the constant neighborhood near the edge may also change. The change is related linearly to the length of the impulse and inversely to the length k. This is exemplified in Fig. 2 where an input signal consisting of an edge and an impulse ($l = 1$) is filtered with the SM filter and the FMH filter of (1) with $k = 5$.

The output of the SM filter is all the time one of the input values. Some binary oscillation may, therefore, remain intact although the filtering is repeated many times [4]. The FMH filters generate also new values which are between the minimum and maximum values of the original signal. If the length k in (1) is an exact multiple of the period of a binary oscillation, the output of the FMH filter converges to the average of the values in the binary oscillation with one filtering operation. If k is not an exact multiple of the oscillation period, the amplitude of the oscillation is attenuated exponentially with repeated filterings. The root signals of the SM and FMH filters are analyzed more thoroughly in [8].

IV. Noise Attenuation

In this section, we compare the noise attenuation properties of the SM and FMH filters when a symmetrically distributed noise is added to a constant valued signal.

For the identically and independently distributed (i.i.d.) input noise, the probability density function of the output of a SM filter is [4]

$$f_{SM}(y) = \frac{N!}{k!k!} f(y) \left[F(y)\right]^k \left[1 - F(y)\right]^k \quad (4)$$

where $N = 2k + 1$ is the length of the filter window, and $f(\cdot)$ and $F(\cdot)$ are the probability density and distribution functions of the input signal, respectively.

In the FMH filter with $M = 3$, the median is taken over three values y_1, y_2, and y_3 which all may have different probability density functions. It can be shown that the density function of the output in that case becomes

$$\begin{aligned} f_{FMH3}(y) &= F_1(y) \cdot f_2(y) \cdot \left(1 - F_3(y)\right) \\ &\quad + F_3(y) \cdot f_2(y) \cdot \left(1 - F_1(y)\right) + f_1(y) \\ &\quad \cdot \left[\left(1 - F_2(y)\right) F_3(y) + F_2(y) \right. \\ &\quad \left. \cdot \left(1 - F_3(y)\right)\right] \\ &\quad + f_3(y) \left[\left(1 - F_2(y)\right) F_1(y) + F_2(y) \right. \\ &\quad \left. \cdot \left(1 - F_1(y)\right)\right]. \end{aligned} \quad (5)$$

For the FMH filter with $M = 5$, we consider only the symmetrical situation where $f(y_1) = f(y_5) = f_1(\cdot)$, $f(y_2) = f(y_4) = f_2(\cdot)$, and $f(y_3) = f_3(\cdot)$ corresponding to the FMH filter of (2) and (3) operating on a constant neighborhood with superimposed white noise. Note that for the FMH filter of (2), $f_2(\cdot) = f_3(\cdot)$, and for FMH filter of (3) $f_1(\cdot) = f_2(\cdot)$ if k is even. In the symmetrical cases, the density function of the output becomes

$$\begin{aligned} f_{FMH5}(y) &= 4F_1(y)F_2(y) \cdot f_3(y) \\ &\quad \cdot \left(1 - F_2(y)\right)\left(1 - F_1(y)\right) \\ &\quad + F_1(y)^2 \cdot f_3(y) \cdot \left(1 - F_2(y)\right)^2 \\ &\quad + F_2(y)^2 \cdot f_3(y) \cdot \left(1 - F_1(y)\right)^2 \\ &\quad + 4F_1(y)F_2(y) \cdot f_1(y) \\ &\quad \cdot \left(1 - F_2(y)\right)\left(1 - F_3(y)\right) \\ &\quad + 2F_1(y)F_3(y) \cdot f_1(y) \cdot \left(1 - F_2(y)\right)^2 \\ &\quad + 2F_2(y)^2 \cdot f_1(y) \cdot \left(1 - F_1(y)\right)\left(1 - F_3(y)\right) \\ &\quad + 4F_2(y)F_3(y) \cdot f_1(y) \\ &\quad \cdot \left(1 - F_1(y)\right)\left(1 - F_2(y)\right) \\ &\quad + 4F_1(y)F_2(y) \cdot f_2(y) \\ &\quad \cdot \left(1 - F_1(y)\right)\left(1 - F_3(y)\right) \\ &\quad + 4F_1(y)F_3(y) \cdot f_2(y) \\ &\quad \cdot \left(1 - F_2(y)\right)\left(1 - F_1(y)\right) \\ &\quad + 2F_1(y)^2 \cdot f_2(y) \cdot \left(1 - F_2(y)\right)\left(1 - F_3(y)\right) \\ &\quad + 2F_2(y)F_3(y) \cdot f_2(y) \cdot \left(1 - F_1(y)\right)^2. \end{aligned} \quad (6)$$

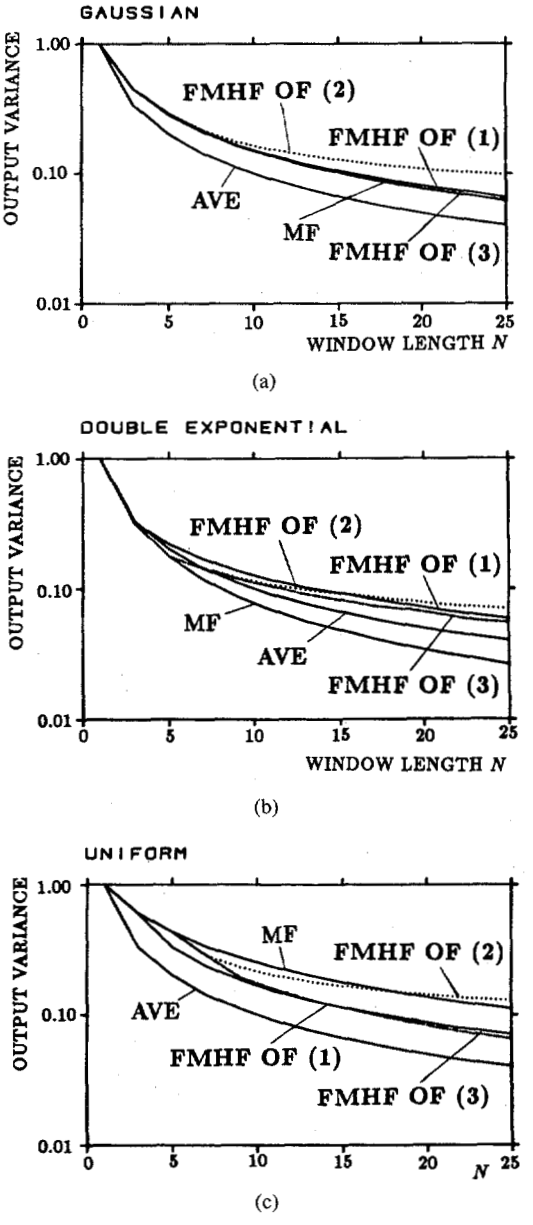


Fig. 3. Output variances versus window length. (a) Gaussian, (b) double exponential, (c) uniform input noise distribution.

Using the equations (4)–(6), we have calculated the output variances of the SM filter and the FMH filters with different window lengths. The input signals were zero mean i.i.d. noise with different distribution functions. The distribution functions of the averages in (1)–(3) were calculated using numerical convolutions. In Fig. 3, the output variances are plotted for Gaussian, double exponential, and uniform input distributions with variance $\sigma_i^2 = 1.0$.

It can be noted that with the Gaussian input distribution, the behavior of the SM and the FMH filters are al-

most identical. With double exponential input distribution, the SM filter is superior to averaging and to FMH filters, but with uniform input distribution, the FMH filters are superior to the SM filters. Due to ease of implementation and good noise attenuation properties, only the FMH filter of (1) will be used hereafter, it will be called the FMH filter where it causes no confusion.

V. Response to Noisy Edges

In noisy conditions, the impulses near the edges change the shape and very often also the location of the edge as was shown above. In this section, we analyze the behavior of the SM and the FMH filters when Gaussian noise is added to a root signal which contains sharp edges. To minimize the effect of the noise near the edges, we also introduce a repeated filtering operation where the length k is increased gradually from one to the desired maximum value. This method is shown to be efficient if the signal is heavily embedded in noise, and it is important to preserve the exact shapes of the sharp edges and also the height of the pulses.

One period of the input signal is shown in Fig. 4 when a zero mean unit variance Gaussian noise $n_{(0,1)}(n)$ has been added to the square wave signal $s_i(n)$. The signal $s_i(n)$ is a root of all the compared filters. The expected values of the mean $m(n)$, standard deviation $\sigma(n)$, and the rms-error $e_{\text{rms}}(n)$ of the output signals have been calculated over 1000 periods. The rms-error is defined as $e_{\text{rms}}(n) = \sqrt{b^2(n) + \sigma^2(n)}$ where $b(n)$ is the bias error and σ^2 is the variance around the mean.

In Fig. 5, we have the statistical values of the output signal over one period when the noisy input signal was filtered once with the SM filter of length $N = 11$. In Fig. 6, SM filtering with $N = 11$ was repeated until the root was found. In Fig. 7, the noisy input signal was filtered once with a cascade of SM filters with $N = 3$, 5, 7, and 9. Thereafter, the root with $N = 11$ was searched. From Fig. 5, it can be seen that although the square wave signal under the noise is a root of the filter, the average output signal becomes almost a triangular wave which is not a root. The root searched directly with $N = 11$ has a high bias error and the edges are highly deteriorated. The root searched with the increasing filter length (Fig. 7) resembles more the original square wave. The bias error is not so large and the edges are sharper.

In Figs. 8–10, we have the statistical output signals of the FMH filters when applied in the same way as above. The filter length N was again 11 to give about the same noise attenuation as the SM filter for a constant signal level with additive Gaussian noise. Note, however, that now the critical root length L_R is 10 for the FMH filter, but only 6 for the SM filter. After one filtering with the FMH filter, the output signal (Fig. 8) statistically resembles more the original square wave $s_i(n)$ than with the SM filter (Fig. 5). The roots searched with the FMH filters (Fig. 9) have larger bias errors than those searched with the SM filter. The edges, however, are at least as

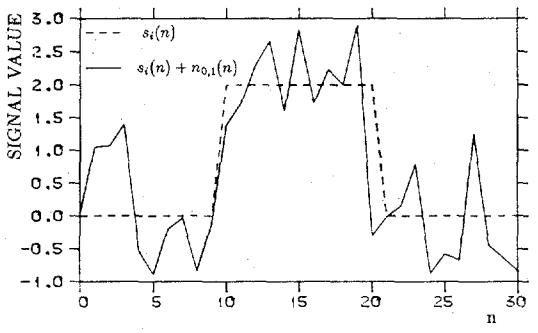


Fig. 4. One period of the noiseless input signal $s_i(n)$ and the signal $s_i(n)$ contaminated by i.i.d. Gaussian white noise with zero mean and unit variance.

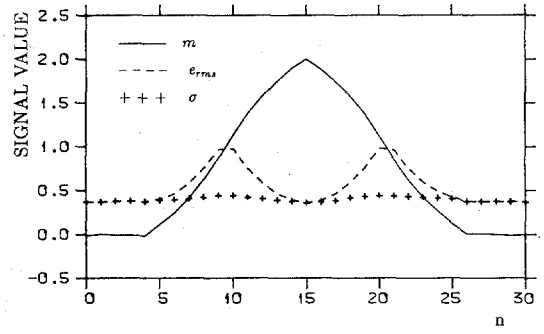


Fig. 5. Average output when the noisy signal of Fig. 4 is filtered once with the SM filter with $N = 11$. $m(n)$ is the mean calculated over 1000 periods, σ is the standard deviation, and $e_{\text{rms}}(n)$ is the rms-error of the output signal.

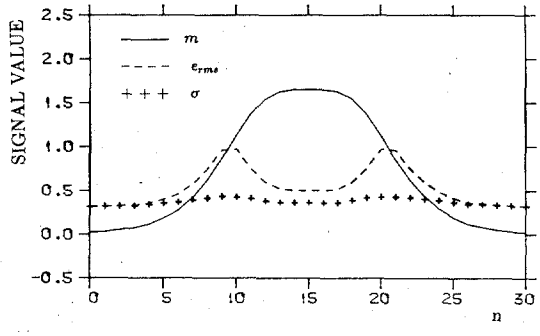


Fig. 6. Average root of signal in Fig. 4 searched with the SM filter with $N = 11$.

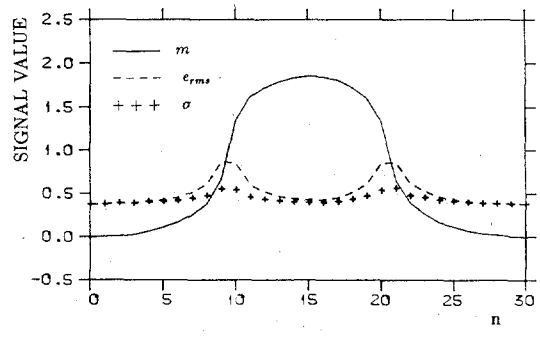


Fig. 7. The signal in Fig. 4 filtered first with the SM filters with $N = 3$, 5, 7, and 9. Thereafter, the root was searched with $N = 11$.

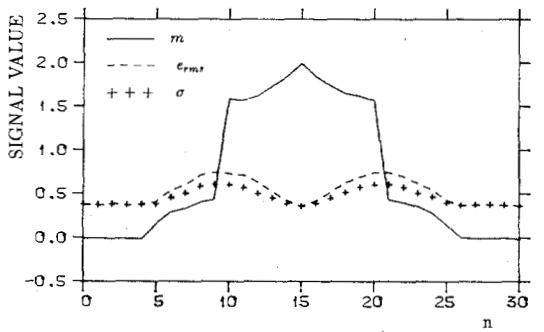


Fig. 8. The signal in Fig. 4 filtered with the FMH filter with $N = 11$.

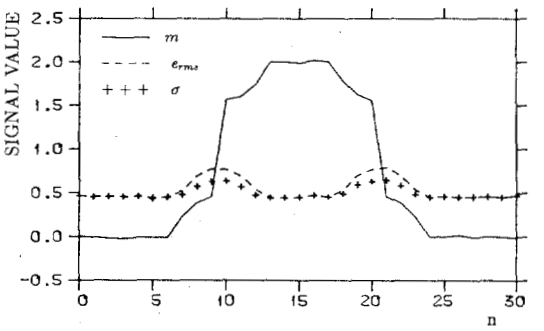


Fig. 11. The signal in Fig. 4 filtered with the FMH filter with $N = 7$.

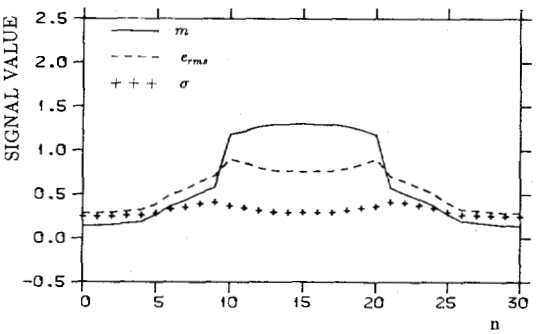


Fig. 9. The root of signal in Fig. 4 searched with the FMH filter with $N = 11$.

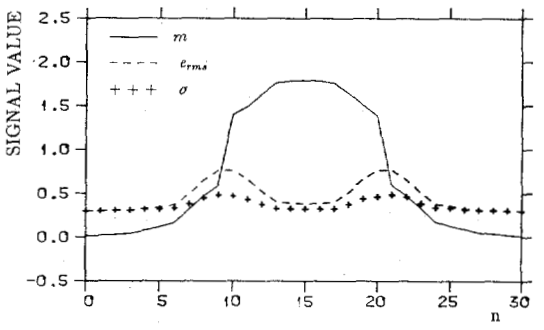


Fig. 12. The root of signal in Fig. 4 searched with the FMH filter with $N = 7$.

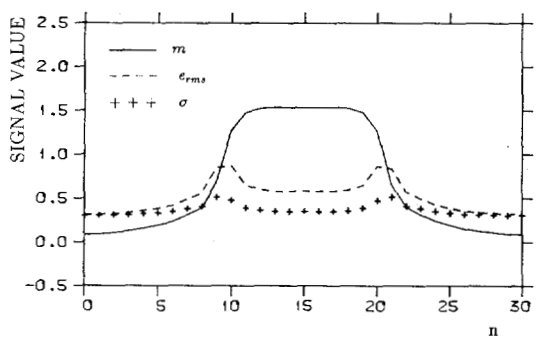


Fig. 10. The signal in Fig. 4 filtered first with the FMH filters with $N = 3$, 5, 7, and 9. Thereafter, the root was searched with $N = 11$.

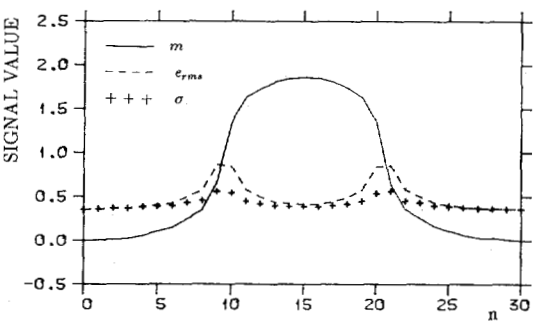


Fig. 13. The signal in Fig. 4 filtered first with the FMH filters with $N = 3$ and 5. Thereafter, the root was searched with $N = 7$.

sharp as with the SM filter. When the signal was first filtered with $N = 3$, 5, 7, and 9, and thereafter the root was searched with $N = 11$, we obtained relatively sharp edges and managed to decrease the bias error (Fig. 10).

In Figs. 11–13, the noisy input signal was filtered with the FMH filters as above but now the length N was 7 to make the root length L_R identical to that of the SM filter with $N = 11$. Now the output signals resemble even more the input square wave. After one filtering (Fig. 11), there is no bias error in the middle area of the pulse and the edges are almost as sharp as in the original square wave $s_i(n)$ of Fig. 4. Searching the root with the FMH filter with $N = 7$ (Fig. 12) causes some bias error, but less than with the SM filter or the FMH filter with $N = 11$ (Fig. 6). The sharpness of the edges is much better than with the SM filter. With increasing filter lengths, the SM filter with $N = 11$, and the FMH filter with $N = 7$, give statistically exactly the same output waveforms (see Figs. 7 and 13). However, with the FMH filters, the amount of computation is substantially less than with the SM filter as will be shown below.

VI. Filter Implementations

When searching the median of N values, the number of data sorting operations in the optimal situation using a modified *Quicksort* may be as low as $\simeq 2N$ [9]. In the worst case, however, when the data are already nearly ordered, the number of needed operations is proportional to N^2. The worst case occurs, for example, in the search of a root signal. In practice, the total number of operations needed in the search of a root signal with the SM filter may be approximated to be of the order $N \log N$ [9].

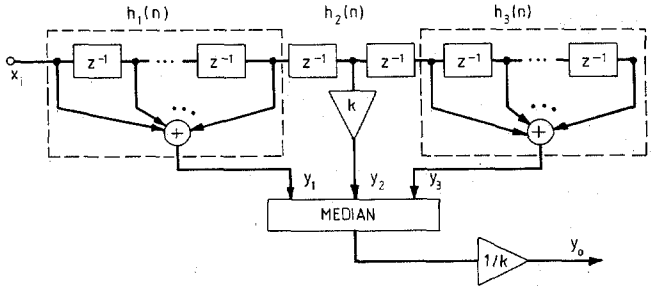


Fig. 14. Implementation of the FIR-median hybrid filter with two nonrecursive averaging substructures.

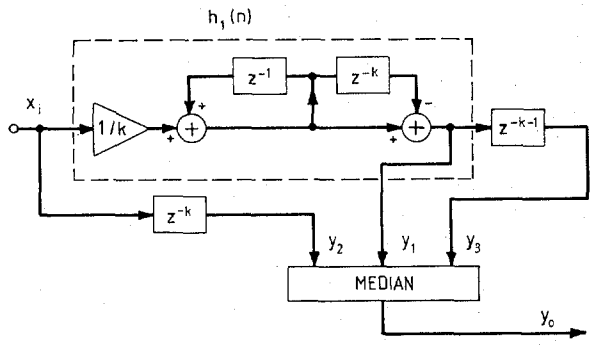


Fig. 15. Efficient implementation of the FIR-median hybrid filter using only one recursive averager.

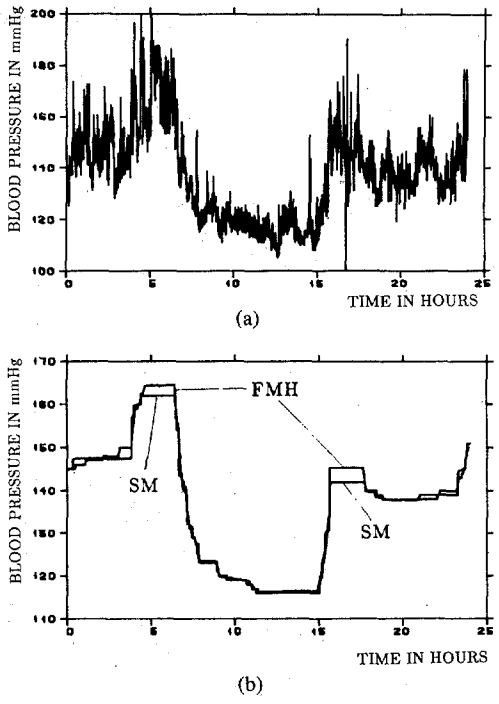


Fig. 16. (a) A long-term blood pressure signal over 24 h. (b) The root signal searched by the SM and the FMH filters.

The FIR subfilters of (1)–(3) can be implemented using nonrecursive or recursive structures as shown in Figs. 14 and 15. The block diagram of Fig. 15 shows an implementation where the identical filters $h_1(n)$ and $h_3(n)$ have been implemented only once, and the output y_3 is generated by delaying the output y_1 appropriately. With the recursive averaging structures, the FMH filter of (1) can be realized with one scaling multiplier, two additions, and three sorting operations per output sample irrespective of the window length $N = 2k + 1$. If the subfilter length k is a power of two, the multiplication can be realized with a shift operation. Using the structure of Fig. 15, the total number of operations (multiplications + additions + sortings) needed to implement the FMH filters of (2) and (3) is 13 and 16, respectively. These values are also independent of the total filter length N. Thus, the FIR median hybrid filters are computationally very efficient and easy to implement using either software or hardware.

VII. Examples

To illustrate the efficiency of the proposed FMH filters over the SM filter, we have searched root signals of a 24-h blood pressure recording of Fig. 16(a). The length L_R of the desired root signal was 241 samples. This is equal to 2 h of samples averaged over 30 s. The recording was started in the afternoon (0.0). In the evening (4–6), the person participated in a very exciting meeting, during the night (8–15) he was sleeping. The next morning (16–18), he gave a lecture and then continued his normal work routines. In Fig. 16(b), we have the found root signals. The roots were searched with an SM filter and with the FMH filter. With both filter types, the roots were searched with increasing filter lengths to keep the edges as sharp as possible. The intermediate and the final root lengths L_R were 31, 61, 121, and 241 data samples, respectively. The output of the SM filter was calculated using a modified *Quicksort*-algorithm to search only the median [9].

It can be noted that the outputs of the FMH and SM filters are almost identical. The root found by the FMH filter seems to resemble the original signal even better than the root of the SM filter. On a VAX-11/780 computer, the CPU time was about 9000 s with 5 iterations for the SM filter. For the FMH filter, with 20 iterations, the CPU time was 150 s with nonrecursive and only about 20 s with recursive subfilters. However, some time was wasted as the implementation used two separate FIR subfilters instead of the structure shown in Fig. 15. The FMH filter thus produced approximately a 450-fold speed increase over the SM filter with about equal filtering performance, although the SM filter requires usually less iterations than the FMH filter to find the root.

VIII. Conclusions

In this paper, we have introduced a new class of generalized median filters which contain linear substructures. The root signal types as well as the noise attenuation properties of these FIR-median hybrid (FMH) filters are similar to those of the standard median (SM) filters. The FMH filters require, however, significantly less computations than the SM filters. In this paper, we have analyzed the properties of some illustrative FMH filters in the one-dimensional case. The example filters were selected to be easy to implement and to have similar types of root

signals as the SM filter has. The method can be applied also to image processing with similar computational benefits [10], [11]. Also, other substructure types are possible. The FMH filters with predictive FIR substructures are analyzed in [12]. These filters are shown to have completely new properties and root signals which cannot be achieved using SM filters.

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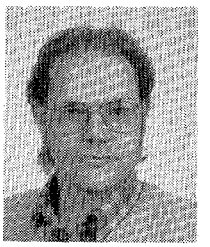
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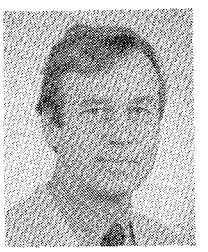
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