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Effect of Finite Impulse Response Filters on Activities of Daily Living Classification Algorithms

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***Abstract*—With the increasing aging population, improving the healthcare system is an important task in every country. The largest number of hospitalizations of the elderly people is due to falls. Therefore, many researchers have come up with different fall detection mechanisms. Improving the accuracy of these algorithms is an important task. This paper focuses on the use of Finite Impulse Response filters to improve the accuracy.**

Keywords— ADL, FIR, Accelerometers, Fall detection.

I. INTRODUCTION

With increasing aged population it is imperative to take actions to improve the healthcare system. The various electronic sensors are now being used to protect the lives of elderly people who are living in their own homes alone. These people are either suffering from impairments or with reduced cognitive ability and mobility due to the age. Electronic sensors attached to the person are used to attract attention of a remote caretaker. Apart from getting external assistance in case of an emergency, monitoring movements of the patient can reduce the chance of reaching emergency situations. Remote activity classification systems can be used to measure degree of functional ability. Tri axial accelerometers can be used to classify these activities. Detecting falls is one major part of these algorithms because falls are one of the main causes of hospitalization for the aged population which can lead to lifelong nursed care, loss of confidence, limiting their mobility and physical activity. Therefore it is essential to have a higher accuracy rates for these algorithms. This paper will focus on finding out the best Finite Impulse Response (FIR) filters to detect falls.

II. BACKGROUND

World population has been projected to increase by 1 billion people within the next 12 years [1]. Population aged 60 or over will increase by 1% annually before 2050 in developed countries, whereas in developing countries it is increasing at a rate of 3.7% per year during 2010-2015 and then by 2.9% per year before 2050. With an ever-increasing aging population, more actions should be taken to improve their quality of life and maintain their health.

Keeping a dedicated person at the side of the patient at home or even in the hospital is not easy and this leads to a need for a tele healthcare system where the patient can be monitored remotely by the healthcare person. This will also help in early diagnosis and this in turn will lead to reduced medical expenditure. Patients with cardiovascular diseases, neurodegenerative disorders can be monitored with this method, and this will also help in detecting falls which is very common in people aged over 65.

It is estimated that 30% of falls are within the people aged 65 and 50% among people over 80 years [2]. As reported in

[3] during 1993-2003, number of fatal falls in USA has a percentage increase of 55.3. Similarly, number of non-fatal falls has increased by 2.8% from 2001-2005. In both scenarios, women recorded a higher number compared to men.

The falls can lead to hospitalization and more often the mobility of the patient will be limited even after treatments. They must live under nursed home care. This limitation to their mobility will also have a psychological effect because of loss of confidence. In a study done in Taiwan it was found that among the falls, around 37% had a repeated fall event [4]. Even if they regain their mobility without much damage from the fall, the risk of falling again will limit their physical activity level.

In view of this many studies have been conducted to find methods to reduce these falls. Among them triaxial accelerometer-based methods to determine the activities of daily living (ADL) [5] are low cost and reliable and were implemented by Mathie et al. on a wearable device [6] for long term monitoring of unsupervised functional status at home. Kangas et al [7] developed fall detection algorithms implemented on head, waist and wrist worn devices and found that waist worn devices are more efficient.

The algorithms developed on these systems play a vital role in detecting these falls by classifying the activities of daily living in real time and it is essential to have a higher accuracy rate. Filters in these algorithms play a vital role in this aspect. This thesis will focus on implementing FIR filters with the window method and it will be used on previously collected data to find the accuracy, sensitivity and specificity and compare that with the performance of the benchmarking filters and developing an algorithm to classify ADL with a neck worn accelerometer.

III. FILTER IMPLEMENTATIONS

Finite Impulse Response (FIR) filters are the most efficient causal filters [12]. This filters can be implemented in real time and because their poles located at the origin of the z plane they are stable. If the filter taps are symmetric about the center tap, they have a linear phase response [14]. If a large number of taps are used FIR filters achieve high roll off rates but this increase the calculation time [8].

FIR filters can be implemented using several methods. They are Window method, Frequency sampling, Parks-McClellan method. Since in Murtagh [9] Parks-McClellan method was used, window method was investigated in this paper.

Difference equation for FIR filter

$$y[k] = \sum_{m=0}^{M-1} h_m x_{k-1}$$

where y[k] = output at time k
x[k] = input at time k
hm = Filter coefficients
M = number of taps = order of filter + 1

For a low pass filter coefficients can be calculated by

$$h_m = 2\frac{f_c}{f_s}\frac{sin\left(2\pi m\frac{f_c}{f_s}\right)}{2\pi m\frac{f_c}{f_s}}$$

For window methods these coefficients should be multiplied with the coefficients found from the relevant window function. In this thesis Hamming, Hann and Blackman windows will be implemented. Filter coefficients are calculated using MATLAB [13].

Hamming window coefficients were found using

$$w(m) = 0.54 - 0.4\cos\frac{2\pi m}{M}$$

The calculated coefficients are shown in Table I.

TABLE I. COEFFICIENTS FOR HAMMING WINDOW

Coefficient	Value	Scaled Value
H0	6.6231	7
H1	5.7925	6
H2	4.5233	5
H3	2.9703	3
H4	1.3181	1
H5	-0.2457	0
H6	-1.5558	-2
H7	-2.4916	-2
H8	-2.9908	-3
H9	-3.0547	7-3
H10	-2.7428	-3
H11	-2.1599	-2
H12	-1.4365	1
H13	-0.7063	1
H14	-0.0859	0
H15	0.3424	0
H16	0.5398	1
H17	0.5131	1
H18	0.3087	0
H19	0	0
H20	-0.3278	0

Hann window coefficients were found using

$$w(m) = 0.5(1 - \cos\frac{2\pi m}{M})$$

The calculated coefficients are shown in Table II.

TABLE II. COEFFICIENTS FOR HANN WINDOW

Coefficient	Value	Scaled Value
H_0	0.2832	0
H_1	1.0939	1
H2	2.3215	2
H3	3.7998	4
H4	5.3314	5
H5	6.7162	7
H6	7.7792	8
H7	8.3944	8
H8	8.4999	8
H9	8.1032	8
H10	7.2759	7
H11	6.1385	6
H12	4.8396	5
H13	3.5317	4
H14	2.3481	2
H15	1.3849	1
H16	0.6906	1
H17	0.2634	0
H18	0.0583	0
H19	0	0
H20	0	0

Blackman window coefficients were found using.

$$w(m) = 0.42 - 0.5cos\frac{2\pi m}{M} + 0.08cos\frac{4\pi m}{M}$$

The calculated coefficients are shown in Table III.

TABLE III. COEFFICIENTS FOR BLACKMAN WINDOW

Coefficient	Value	Scaled Value
H_0	0.1060	0
H_1	0.4546	0
H_2	1.1154	1
H_3	2.1396	2
H_4	3.4979	3
H_5	5.0452	5
H_6	6.5345	7
H_7	7.6773	8
H_8	8.2305	8
H_9	8.0743	8
H_{10}	7.2499	7
H_{11}	5.9439	6
H_{12}	4.4262	4
H_{13}	2.9660	3
H_{14}	1.7639	2
H_{15}	0.9086	1
H16	0.3888	0
H17	0.1265	0
H18	0.0242	0
H19	0	0
H20	0	0

Accelerometer with a sample rate of 40Hz and a barometric pressure sensor with a sampling rate of 1.8Hz was used. Previously collected data [10] which were obtained from 20 young actors performing stimulated falls as shown in fig 19 was used in the testing. Testing of the FIR windowed filters for accuracy, sensitivity and specificity was carried out on the algorithm used by Wang et al [11]. Elliptical filter and Butterworth filter for acceleration and pressure data was used in the benchmark implementation.

TABLE IV. EXPERIMENTAL PROTOCOL

Sequence	Category	Instructions
1	Fall	Forward fall, ending lying
2	Fall	Backward fall. Ending lying
3	Fall	Lateral fall, ending lying
4	Fall	Forward fall, ending active lying
5	Fall	Forward fall with attempt to break the fall
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position
7	Fall with recovery	Forward fall, recovery and walking
8	Fall with recovery	Forward fall, recovery and standing
9	No Fall	Sitting on a chair
10	No Fall	Collapse into a chair
11	No Fall	Climbing into bed
12	No Fall	Jump in vertical direction
13	No Fall	Pick up something from the floor
14	No Fall	Bend down and doing own laces
15	No Fall	Taking the lift (one floor, down)
16	No Fall	Walk down trhe stairs (6 steps)

IV. RESULTS

Number of correctly and incorrectly classified falls are shown in below figures for each filter. Accuracy, specificity and sensitivity of each of these filters were compared to Bianchi algorithm and Wang algorithm.

Figures 1, 2, 3, and 4 show the classified results using the Wang algorithm [11].

			Hamming		
No	Category	Instructions	Overall Correct	Overall Incorrect	Accuracy (%)
1	Fall	Forward fall, ending lying	20	0	100
2	Fall	Backward fall, ending lying	20	0	100
3	Fall	Lateral fall, ending lying	20	0	100
4	Fall	Forward fall, ending active lying	18	2	90
5	Fall	Forward fall with attempt to break the fall	16	4	80
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position	17	3	85
7	Fall with recovery	Forward fall, recovery and walking	18	2	90
8	Fall with recovery	Forward fall, recovery and standing	19	1	95
9	No fall	Sitting on a chair	20	0	100
10	No fall	Collapse into a chair	17	3	80
11	No fall	Climbing into bed	20	0	100
12	No fall	Jump in vertical direction	20	0	100
13	No fall	Pick up something from the floor	20	0	100
14	No fall	Bend down and doing own laces	20	0	100
15	No fall	Taking the lift	20	0	100
16	No fall	Walk down the stairs (6 steps)	20	0	100

Fig. 1. Test results for Hamming window

			Hann		
No	Category	Instructions	Overall Correct	Overall Incorrect	Accuracy (%)
1	Fall	Forward fall, ending lying	20	0	100
2	Fall	Backward fall, ending lying	20	0	100
3	Fall	Lateral fall, ending lying	20	0	100
4	Fall	Forward fall, ending active lying	18	2	90
5	Fall	Forward fall with attempt to break the fall	17	3	85
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position	17	3	85
7	Fall with recovery	Forward fall, recovery and walking	18	2	90
8	Fall with recovery	Forward fall, recovery and standing	19	1	95
9	No fall	Sitting on a chair	20	0	100
10	No fall	Collapse into a chair	14	6	70
11	No fall	Climbing into bed	19	1	95
12	No fall	Jump in vertical direction	20	0	100
13	No fall	Pick up something from the floor	20	0	100
14	No fall	Bend down and doing own laces	20	0	100
15	No fall	Taking the lift	20	0	100
16	No fall	Walk down the stairs (6 steps)	20	0	100

Fig. 2. Test results for Hann window

			Benchmark		
No	Category	Instructions	Overall Correct	Overall Incorrect	Accuracy (%)
1	Fall	Forward fall, ending lying	20	0	100
2	Fall	Backward fall, ending lying	20	0	100
3	Fall	Lateral fall, ending lying	20	0	100
4	Fall	Forward fall, ending active lying	19	1	95
5	Fall	Forward fall with attempt to break the fall	18	2	90
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position	18	2	90
7	Fall with recovery	Forward fall, recovery and walking	9	11	45
8	Fall with recovery	Forward fall, recovery and standing	12	8	60
9	No fall	Sitting on a chair	7	13	35
10	No fall	Collapse into a chair	3	17	15
11	No fall	Climbing into bed	16	4	80
12	No fall	Jump in vertical direction	14	6	70
13	No fall	Pick up something from the floor	20	0	100
14	No fall	Bend down and doing own laces	19	1	95
15	No fall	Taking the lift	20	0	100
16	No fall	Walk down the stairs (6 steps)	20	0	100

Fig. 3. Test results for Blackman window

			Blackman		
No	Category	Instructions	Overall Correct	Overall Incorrect	Accuracy (%)
1	Fall	Forward fall, ending lying	20	0	100
2	Fall	Backward fall, ending lying	20	0	100
3	Fall	Lateral fall, ending lying	20	0	100
4	Fall	Forward fall, ending active lying	18	2	90
5	Fall	Forward fall with attempt to break the fall	18	2	90
6	Fall	Resting against a wall, then sliding vertically down to the end in the sitting position	17	3	85
7	Fall with recovery	Forward fall, recovery and walking	17	3	85
8	Fall with recovery	Forward fall, recovery and standing	19	1	95
9	No fall	Sitting on a chair	19	1	95
10	No fall	Collapse into a chair	12	8	60
11	No fall	Climbing into bed	20	0	100
12	No fall	Jump in vertical direction	20	0	100
13	No fall	Pick up something from the floor	20	0	100
14	No fall	Bend down and doing own laces	20	0	100
15	No fall	Taking the lift	20	0	100
16	No fall	Walk down the stairs (6 steps)	20	0	100

Fig. 4. Test results for Benchmark algorithm

Table V shows the accuracy, sensitivity and specificity of each filter compared with the benchmark implementation. Hamming windowed FIR filter gives out the highest accuracy, specificity and sensitivity among all the filters. When compared to the benchmark implementation using the Wang

[11] algorithm Hamming filter has the highest rate of accuracy, sensitivity and specificity.

TABLE V. SUMMARY OF RESULTS

%	Blackman	Hann	Hamming	Benchmark
Accuracy	93.75	94.69	95.31	79.69
Sesitivity	94.30	96.13	98.01	76.84
Specificity	93.21	93.33	92.90	83.22

V. DISCUSSION

This paper has investigated the effects of windowed FIR filters on Wang [11] algorithm. FIR filters can be designed using window method, frequency sampling method and optimal filter method. In the first part of this thesis Blackman, Hamming and Hann windows were implemented and their performances were evaluated using a fall detection algorithm. Newly designed filters were compared with benchmark implementations of Butterworth and elliptical filter. When comparing all the thresholds of the algorithms were kept at the same level. As shown in Fig. 1 using Hamming window accuracy, sensitivity and specificity has increased to 95.31%, 98.01% and 92.90% respectively compared to the benchmark implementation.

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