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Identifying the Gestures of Toddler, Pregnant Woman and Elderly using Segmented Pigeon Hole Feature Extraction Technique and IR-Threshold Classifier

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Abstract

Objectives: The Objective of this research is to develop a feature extractor and a classifier which will identify and classify the gestures of infants, elderly and pregnant woman using Gait Signal re-ceived from wearable electrodes which is positioned on the body of subjects. **Methods/Statistical Analysis:** Remote health care monitoring is a technology which enables monitoring a person outside usual medical settings i.e., in the house or residence, which may increase access to caretakers or person at home but it will decrease healthcare deliverance costs. **Findings**: A novel segmented pigeon hole data extraction and reduction technique is proposed for reducing data and feature extraction. Secondly an Iteration Reduced Threshold based Classifier (IR-Threshold Classifier) has been introduced, which classifies the reduced extracted data into Safe and Danger for toddler, Normal and contra for pregnant women and Stable and Fall for elderly. Feature extraction and reduction using Segmented Pigeon Hole algorithm reduced the dataset for this domain. It is compared with bench mark data set and it had produced the significant data reduction. The IR Threshold classifier had shown 95% of accuracy when compared with the other classifiers. **Applications/Improvements:** This gives the best predominant electrode set by reducing data which will increase the classification accuracy.

Keywords: Fall and Normal Category, Feature Extraction, IR-Threshold Classifier, Machine Learning Algorithm, Segmented Pigeon Hole, Wearable Electrodes

1. Introduction

Falls are the main source of deadly and non-lethal wounds in elderly. At regular intervals i.e., every 14 seconds, an older adult is dealt with in the crisis space for a fall; and in every 29 minutes, elderly bumps in the bucket and fall for a fall-related damage according to insights. Falls are the real issue in the elderly individuals. Twenty to thirty percent of individuals who fall endure direct to extreme wounds, for example, hip and leg cracks and head injuries. These wounds make it hard for elderly individual to live autonomously without others help and which likewise expands the danger of death. Fall are driving reason for both deadly and non-lethal issues. Numerous individuals, who fall, regardless of the possibility that they are not harmed, they build up a dread of falling. This dread may make them constrain their exercises, which prompt lessened portability and loss of physical wellness and thereby increment their genuine danger of falling. Keeping in mind the end goal to decrease such incidents from happening, different fall recognition arrangement have been proposed before. In this paper, the idea of information mining and machine learning ideas are utilized to propose a practical system that is a classifier to characterize the mimicked elderly fall

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data sets. In the wake of arranging the information sets it can be the contribution to a gadget which can alert the overseer. Information mining.1 is an interdisciplinary sub field of software engineering used to mine examples from an expansive information set. The general objective of the information mining procedure is to concentrate data from an information set and change it into a justifiable structure for further utilize. Machine learning is logical study that arrangements with the development and investigation of the calculation that can gain from the give information. The rest of the paper is organized as follows: Section 2 details related works. Section 3 describes the methodology. Section 4 explains the system architecture in detail. Section 5 illustrates about the system analysis. Section 6 explains the detailed implementation. Section 7 Discusses about the results and Section 8 concludes with conclusion and future enhancements of the paper.

2. Related Works

Various monitoring posture recognition and fall discovery arrangements have been produced to make a solid framework for elderly individuals mainly and very few for normal toddlers and pregnant women. For toddlers there are monitoring techniques for children with cerebral palsy etc and pregnant woman who are with many complications like high pressure and sugar and are admitted to the hospital where they have measures to monitor them in clinic. But for normal toddler and woman i.e., they don't require 24x7 medical care with no much complexity there are no such technique to monitor them when they are alone at home. With the reason to effectively recognize the risks, there are principally three sorts of identification strategy, to be specific wearable device, vision methods and ambient techniques.

2.1 Wearable based Methods

In[2,3] wearable devices are based on smart sensors processing. The sensors are embedded on garments worn. Wearable detectors uses the accelerometer and tilt sensors which is used to monitor velocity, acceleration which is based on the motion of fall or pain. In[9] home health care services sentinel framework, a three stage identification conspire which comprised of an accelerometer, audio, picture and video cuts. Its advancement was to identify falls by utilizing a tri pivotal accelerometer, speech recognition and on request video. In this, once the fall or threat occasion was identified, a alert email was instantly sent and the fall video was transferred to the system stockpiling for further examination. The wearable fall location framework in view of accelerometer fall identification calculations were found to be low in affectability and specificity on genuine falls or threat than in test environment.

2.2 Vision based Methods

In[2,3] vision based method includes real time monitoring and videos based fall detection system. The vision based techniques are identified with spatiotemporal components, change of shape and stance. The vision based fall location framework recognizes fall by applying background subtraction to extricate the closer view human body. The system analyze the human shape deformation and posture recognition in a video sequence to detect fall. PC vision based fall recognition framework for checking an elderly individual in home care application. Foundation subtraction was connected to extract the foreground human body and the outcome is improvised by utilizing certain post preparing. To distinguish a fall, data was sustained into a coordinated acyclic graph support vector machine for stance acknowledgment. The framework is blocked by numerous moving articles and impediments which can be tended to by utilizing a different camera conspire. Vision based strategies are more precise than wearable based and surrounding based techniques. These framework regularly experience the ill effects of high danger of security and the restrictive cost actualizing the cameras.

2.3 Ambient based Methods

In[2,3] ambient based techniques more often than not depend with respect to weight sensors, acoustic sensors or infrared movement sensors implemented around overseers' home[5,6]. The fall discovery sensors are linear arrays of electrode condenser or circular array of microphones placed on a pre-amplifier board. Based on the direction of source such as sound or vibration, the system detects the fall of an elderly person. Verity, two part framework which had a based station and direct observing gadget. Utilizing a ultra-low power sensor interface and RF correspondence, encompassing/skin temperatures are measured for constant checking. Because of the high measurement and non-linearity of the gathered sensor information, a classifier with dimensional reduction system was proposed. The classifier was developed based in the Curvilinear Distance Analysis. The proposed classifier outperforms the conventional classifier in its one-pass training and with higher distinguishes capability. Ambient based method relay on sensors which were usually implemented in and around the home environment. Hence any change in the surrounding environment causes interference with the system.

Other related work for classification is given as measurable components separated from the Region of Interest (ROI) of the breast pa-renchyma locale. K-NN with three diverse separation measurements specifically Euclidean, Cosine, City-block and its mix is utilized for arrangement. The extricated components are sustained into the classifier to arrange the ROI into any of three breast tissue classes, for example, thick, greasy, glandular. The order precision acquired for consolidated k-NN is 91.16%.8. The respiratory flag is characterized into three states, for example, ordinary breath, movement relics, and rest apnea and it is acquired from a physionet, the training of SVM, a binary classifier used to solve multiple class problems is done with the same data set and classification is made to reduce overall errors[9].

3. Methodology

3.1 Wearable Attire and Experiments

3.1.1 Toddlers

An arrangement of 14 electrodes fixed on the wearable coat of the subjects were utilized to record the body development signs and estimations were taken for 5000 milli-seconds (5 seconds) in standard interims. There were 5 subjects chosen for this test, where the average age of them is 3. The recorded signs were standardized and the information was tested at 1024 Hz. The information caught for this investigation were acquired from the ten trials of obtaining led for each of the 5 toddlers amid their consistent play in the safety zone of their play room. The trials were directed with a helpful interim and the information were recorded for

Table 1. Electrode Positions of Toddler, Pregnant woman and elderly

	Electrode 1	Electrode 2	Electrode 3	Electrode 4	Electrode 5	Electrode 6	Electrode 7
Toddler	Left Shoulder	Left Ankle	Left Palm	Right Shoulder	Right Ankle	Right Palm	Left thigh
Pregnant Woman	Centre	Upside Right	Middle side right	Lower side right	Upside left	Middle side left	Lower side Left
Elderly	Left upper arm	Left middle arm	Left lower arm	Lower hip back	Lower hip front	Right upper arm	Right middle arm

	Electrode 8	Electrode 9	Electrode 10	Electrode 11	Electrode 12	Electrode 13	Electrode 14
Toddler	Left knee	Left foot	Right thigh	Right knee	Right foot	Centre chest	Middle Back
Pregnant Woman	Middle Lower Left	Middle Lower Centre	Middle Lower right	Top Left	Top Center	Top Right	Lower Back
Elderly	Right lower arm	Left upper leg	Left knee	Left foot	Right upper thigh	Right knee	Right foot

4 to 5 seconds. The electrodes positioned are shown in the Table 1. In this research work we considered all subjects and involved the data from all trials for the experimental analysis[10,11].

3.1.2 Pregnant Women

An arrangement of 14 electrodes settled on the wear-capable slip belt of the subjects were utilized to record the mid-region development signs and estimations were taken for 5000 milliseconds (5seconds) in general interims. The crude flag information were recorded from the wearable observing interface of the subjects by 14 anodes. Information got from 14 cathodes have bigger values henceforth the information must be standardized. Besides, the information were down sampled to a successful inspecting recurrence of 64 Hz from 1024Hz,the average age of pregnant women is 30.5. The electrode positions as a wearable slip belts and the positions are shown in Table 1[10,11].

3.1.3 Elderly

The Subjects of are old adults of average age 70. There are 10 Subjects involved in this system. The Data from the subjects are acquired using an array of 14 electrodes strapped into a wearable attire which are made using lycra material to suit the individuals of variable body dimensions without much strain to them. The Electrodes are embedded in the wearable attire and appropriately fit to different but specific locations on the subjects. The electrode positions are given in Table 1. The Data acquired using 14 electrodes from the five subjects in a frequency of an entry per 16 milliseconds and for 4-5 seconds approximately on every normal as well as fall trial[10,11].

4. System Architecture

The proposed system is a wearable based system. The system architecture comprise of wearable attire, automated device and triggering device. The Figure 1 shows the fall detection methods. The Figure 2 illustrates the system architecture diagram.

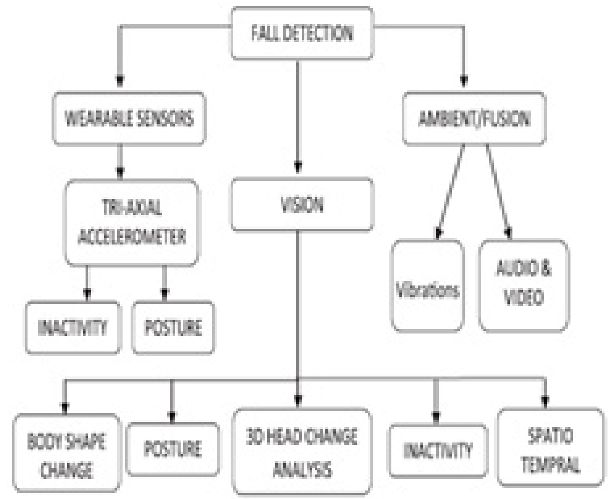

Figure 1. Classification of fall detection methods.

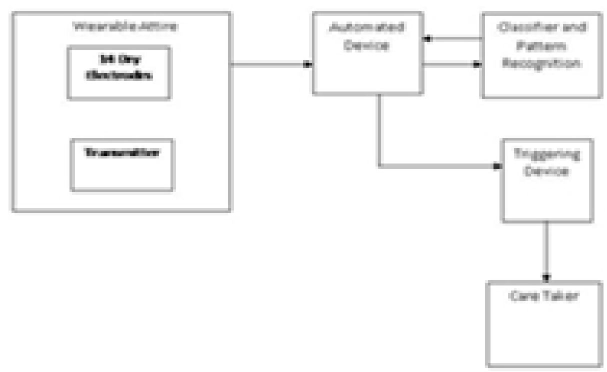

Figure 2. System architecture diagram.

4.1 Wearable Attire

The wearable attire is made up of made up of a polymer based material called Lycra. The attire has 14 dry electrodes statistically placed which reads the kinematic and muscle movement of the elderly person and transmitter transmits these reading to an automated device.

4.2 Automated Device

The automated device receives the signals reading from the transmitter. The automated device receives reading for every 16 ms. The device then provides this reading to classifier and pattern recognition device that analyses the signal data received from the wearable attire.

4.3 Classifier and Pattern Recognition

The classifier and pattern recognition uses a classifying algorithm to classify the dataset into classes and recognize any abnormalities in the signal reading. The concept of machine learning and pattern recognition is used to on the signal dataset of the elderly people. Then upon identifying any abnormalities it notifies a triggering device.

4.4 Triggering Device

The triggering device notifies the concern care taker upon the identification of abnormal dataset reading by the classifier and pattern recognition. The trigger may be an alarm signal to the care taker. The care taker upon getting the alarm signal can attend the elderly people in distress.

5. System Analysis

Wearable attire is a belt in abdomen of pregnant woman and an attire for toddlers and elderly which is used by the proposed system. The wearable attire is made up of a polymer based material called as Lycra. This polymer based wearable attire is worn by three different experimental subjects. The wearable attire is composed 14 dry electrodes that are statistically placed on the wearable electrodes. These electrodes are readers of the kinematic and muscle movements of the body of an elderly, toddler and pregnant woman. These electrodes detect the muscles and skin contraction. These readings are then sent to a transmitter that is also attached on the attire. The transmitter transmits the signal reading to portable analog to digital convertor and data has been collected which can be further used for identifying fall and normal category. The system uses an algorithm to classify and recognize the patterns in the signal reading[12]. The systems classify the data sets into two classes that are safe and danger for toddler, normal and contra for pregnant women and stable and fall for elderly, thresholds are used to provide the decision condition for the system to classify the data sets. The system takes input checks and classifies the data based on the values[13].

6. Implementation

The proposed system implementation comprises of a novel feature reduction and extractor for the signals received from wearable electrodes and then to design a novel classifier which classifies the dataset into safe and danger for toddler, normal and Contra for Pregnant woman and stable and fall for elderly. The first part of the system implementation technique is the feature reduction and extractor. Feature reduction measurement decrease is the way toward lessening the quantity of random variables under consideration. Include extraction changes the information in the high-dimensional space to a space of less measurements. It is also the process where accurate data required for the computation by the system are analyzed. In the proposed technique feature extraction and the dimensionality of data is reduced as a combined step and it's an easy process for the system. When the input is fed to an algorithm, the size of the data is reduced and extracted to an acceptable format.

Segmented Pigeon Hole Optimization Technique

The word pigeon hole is taken from the discrete mathematical principle where n items are put into m containers, with $n > m$, then at least one container should contain not less than one item[1]. In this technique the data set is divided into 10 rows and 4 columns to form a segment called a pigeon hole. The last two pigeon holes are formed by the electrodes 13 and 14 which is placed on Chest and centre back for toddler, and electrodes 1 and 2 which is placed in centre and top right for pregnant women and elderly, which by visualization of data there is no much change in the muscular movement signals drawn from the wearable electrodes and when plotted the input signal plot of these two electrodes didn't show any change between the criteria's. Hence the last two electrodes are not taken into consideration for further experiments

In order to have a uniformity the features are taken between the 10 to 90 percent of the signal blocks ie the first 10 percent and the last 10 percent of the signal were considered as omitted area. The signal size is maintained as 250 samples or rows per sample throughout the experiment for all categories. This was done uniformly for both categories of safe and danger for toddler, normal and contra for pregnant woman and stable and fall category for elderly feature signal matrix. The dimension

EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10	EC11	EC12	
LS	LA	LP	RS	RA	RP	LT	LK	LF	RT	RK	RF	
844	1015	2031	1550	1587	1512	1510	1782	2623	1964	2424	1212	
844	1014	2028	1549	1587	1508	1506	1777	2623	1962	2424	1212	
842	1013	2026	1547	1588	1504	1502	1772	2623	1958	2424	1212	
841	1011	2022	1544	1587	1499	1497	1768	2621	1953	2424	1212	
839	1010	2020	1535	1586	1493	1491	1762	2618	1945	2424	1212	SPHi
835	1008	2016	1531	1586	1485	1487	1758	2614	1938	2427	1213	
832	1007	2014	1527	1587	1486	1484	1754	2611	1931	2431	1215	
825	1007	2015	1524	1588	1485	1483	1753	2611	1925	2432	1216	
821	1007	2015	1522	1589	1485	1483	1752	2611	1921	2432	1216	
819	1008	2016	1522	1589	1485	1483	1753	2612	1918	2432	1216	
818	1008	2017	1521	1588	1485	1483	1754	2613	1916	2432	1216	
818	1009	2018	1522	1589	1485	1483	1755	2613	1916	2432	1216	
819	1011	2022	1527	1589	1488	1486	1765	2617	1920	2432	1216	
823	1012	2025	1533	1587	1491	1489	1774	2621	1926	2432	1216	
825	1012	2025	1533	1587	1491	1489	1774	2621	1926	2432	1216	
825	1013	2027	1540	1586	1495	1493	1782	2623	1933	2432	1216	
830	1014	2028	1546	1586	1498	1496	1789	2623	1939	2432	1216	
835	1015	2031	1551	1587	1504	1502	1793	2623	1952	2431	1215	
838	1016	2032	1555	1587	1508	1506	1796	2623	1957	2430	1215	
840	1016	2033	1563	1591	1514	1510	1799	2623	1965	2430	1215	
847	1017	2034	1565	1591	1513	1511	1799	2623	1967	2430	1215	
849	1017	2034	1565	1592	1511	1509	1795	2623	1966	2429	1214	
849	1015	2031	1560	1591	1506	1504	1787	2623	1962	2429	1214	
848	1013	2026	1554	1588	1500	1498	1779	2620	1955	2429	1214	
846	1010	2021	1548	1587	1495	1493	1771	2617	1947	2431	1215	
844	1008	2017	1541	1585	1491	1489	1764	2611	1938	2431	1215	
840	1008	2016	1536	1584	1488	1486	1758	2609	1929	2432	1216	

Figure 3. Segmented pigeon hole of data matrix.

EC1	EC2	EC3	EC4	EC5	EC6	EC7	EC8	EC9	EC10	EC11	EC12	
LS	LA	LP	RS	RA	RP	LT	LK	LF	RT	RK	RF	
818	1008	2017	1521	1588	1485	1483	1754	3613	2916	3432	2216	
818	1009	2018	1522	1589	1485	1483	1755	3613	2916	3432	2216	
819	1011	2022	1527	1589	1488	1486	1765	3617	2920	3432	2216	
823	1012	2025	1533	1587	1491	1489	1774	3621	2926	3432	2216	SPHj
825	1012	2025	1533	1587	1491	1489	1774	3621	2926	3432	2216	
825	1013	2027	1540	1586	1495	1493	1782	3623	2933	3432	2216	
830	1014	2028	1546	1586	1498	1496	1789	3623	2939	3432	2216	
835	1015	2031	1551	1587	1504	1502	1793	3623	2952	3431	2215	
838	1016	2032	1555	1587	1508	1506	1796	3623	2957	3430	2215	
840	1016	2033	1563	1591	1514	1510	1799	3623	2965	3430	2215	
847	1017	2034	1565	1591	1513	1511	1799	3623	2967	3430	2215	
849	1017	2034	1565	1592	1511	1509	1795	3623	2966	3429	2214	
849	1015	2031	1560	1591	1506	1504	1787	3623	2962	3429	2214	
848	1013	2026	1554	1588	1500	1498	1779	3620	2955	3429	2214	
846	1010	2021	1548	1587	1495	1493	1771	3617	2947	3431	2215	
844	1008	2017	1541	1585	1491	1489	1764	3611	2938	3431	2215	
840	1008	2016	1536	1584	1488	1486	1758	3609	2929	3432	2216	
838	1007	2015	1530	1584	1484	1482	1754	3608	2921	3432	2216	
835	1008	2016	1527	1584	1481	1479	1754	3608	2913	3434	2217	
833	1008	2017	1526	1585	1480	1478	1754	3608	2910	3435	2217	
831	1009	2019	1525	1586	1480	1478	1755	3608	2909	3435	2217	
831	1010	2020	1527	1586	1482	1480	1758	3608	2910	3435	2217	
832	1011	2023	1536	1582	1485	1483	1774	3608	2918	3433	2216	

Figure 4. Segmented pigeon hole of data matrix from 14 electrodes for danger zone in toddler.

of each feature signal, A was n by m, where n was the number of electrodes and m was the number of sequential samples in one signal set. So per pigeonhole n = 4, and m = 10. n and m were fixed as this uniformly for both categories of the experiment as shown in Figure 3 and Figure 4.

Algorithm: Segmented Pigeon Hole Algorithm

Input : Data Signal Matrix

Output :Reduced data representation, Difference value between two test classes

Segment or Partition the data signal matrix of Safe, Normal and Stable as DM1 and Danger, Contra and Fall as DM2 from the 'C' electrodes from the attire.

For each partitioned DM1 let $\mathbf{m} \in \mathbf{DM1}$ and $\mathbf{n} \in \mathbf{DM1}$

where $\mathbf{m = 10\ and\ n = 4}$ and $\mathbf{n \leq i \geq m}$

and

For each partitioned DM2 let $\mathbf{m} \in \mathbf{DM2}$ and $\mathbf{n} \in \mathbf{DM2}$

where $\mathbf{m = 10\ and\ n = 4}$ and $\mathbf{n \leq i \geq m}$

Each Partition is represented as Pigeon hole $\sum_{i=1}^{n} \mathbf{PH_i}$ for each {s,N,S},where s=Safe,N=Normal and S=Stable of all the three domains and for each Partition is represented as Pigeon hole $\sum_{j=1}^{n} \mathbf{PH_j}$ for each {D,C,F) where D = Danger, C = Contra and F = Fall of all the three domains

Segment or Partition the Data Matrix (DM1) of Safe, Normal and Stable and Danger, Contra and Fall as DM2 from the 'C' electrodes from the attire where C = 14.

For each data matrix DM

let $\mathbf{m} \in \mathbf{DMi}$ && $\mathbf{n} \in \mathbf{DMi}$

where $\mathbf{m = 10\ and\ n = 4}$ and $\mathbf{n \leq i \geq m}$

.

For each Partition $\sum_{i=1}^{n} \mathbf{SPH_i}$ in normal activity

For each $\sum_{j=1}^{n} \mathbf{SPH_j}$ in abnormal activity

do

Compute mean vector x and y

$$mean(dm): m = \frac{1}{N}\sum_{i=1}^{N} dm_i$$

compute variance of x and y

$$variance(dm):\ \partial^2 = \frac{1}{N}\sum_{i=1}^{N} [(dm]_i - m^2)$$

compute variance of x and y

$$skewness(dm):\ \nabla = \frac{1}{N}\sum_{i=1}^{N} [(dm]_i - m^3)$$

then

Compute the distance between the features x and y is

calculated as

$$s_m = \sum_{i=1}^{n}(x_i - y_i) \quad \&\&$$

$$s_v = \sum_{i=1}^{n}(x_i - y_i) \quad \&\&$$

$$s_s = \sum_{i=1}^{n}(x_i - y_i)$$

. Calculate first four

$$C_{\downarrow}xy = \max(sum(s_{\downarrow}m + s_{\downarrow}v + s_{\downarrow}s)$$

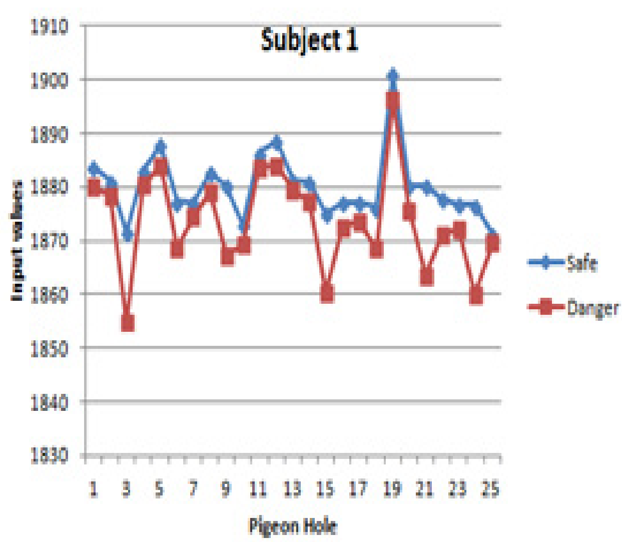

Figure 5. Data reduction using SPH technique of subject 1 of toddler.

C_{xy} electrodes are taken for classification process

The electrodes 9, 10, 11 and 12 i.e., electrodes placed in left foot, right thigh, right knee and right foot shows maximum difference. The pigeon holes (SPHi) 3, 6, 9, 12, 15, 18, 21 and 24 showed maximum difference compared to the other pigeon holes as shown in Figure 5. Therefore by the algorithm the electrodes which are predominant and gives much muscular contraction in the data set can be taken for classification thus by reducing the dataset. The proposed pigeon hole technique is used to feature extract as well as reduce the data set.

The reduction of data in turn reduce the computation time as well as give accurate classification results. The electrodes which are grouped on segmented pigeon hole technique produced maximum difference between the safe and danger categories of toddlers are formed by electrodes:

9, 10, 11, and 12

Since pigeon holes 3, 6, 9....24 are found to be the best distance makers in terms of their features when classified.

This has been observed in all the ten subjects and hence the maximum electrode group is considered for further classification process.

The electrodes 7, 8, 9 and 10 in pregnant woman showed maximum difference and the pigeon holes 2, 5, 8, 11, 14, 17, 20 and 23 are found to be the best difference makers as shown in Figure 6.

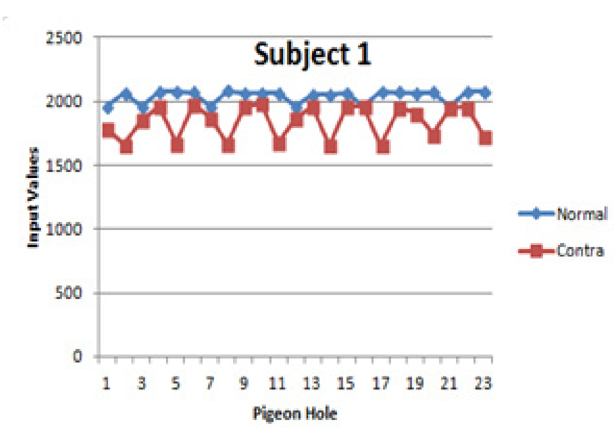

Figure 6. Data reduction using SPH technique of subject 1 of Pregnant Woman.

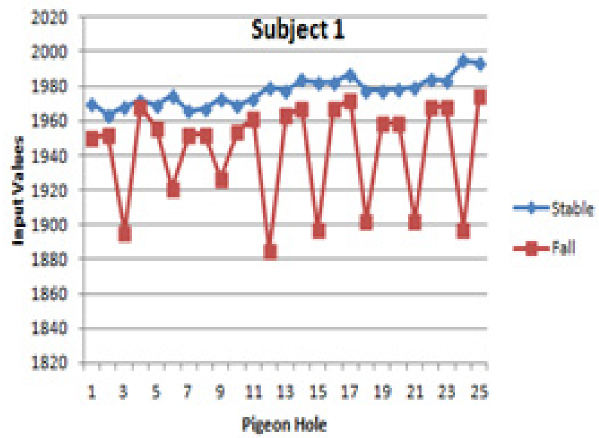

Figure 7. Data reduction using pigeon hole optimization algorithm of subject 1 of elderly.

The electrodes which are grouped on pigeon hole technique produced maximum difference between the stable and fall categories of elderly are formed by the electrodes: 9, 10, 11 and 12 as shown in Figure 7

Since pigeon holes 3, 6, 9....,24 are found to be the best difference makers in terms of features classified and is shown in Figure 6.

Due to Space constraints the output figures is restricted to subject 1 in all three categories. Segmented Pigeon hole Algorithm Compared with Bench mark data for validating the algorithm and to prove that the algorithm is suited for other data sets. Here for that comparison Clinical Gait Data which is well suited for this domain is taken and segmented pigeon hole algorithm is applied.

The results produced are almost same in the percentage of Space savings as compared to the data which is taken for the scope of research.

The results are given in Table 2.

6.1 IR Threshold Classifier

The algorithm proposed and used here is the IR-Threshold Classifier which is fed with two different sets of input. The algorithm classifies the dataset into safe and danger for toddler, normal and contra for pregnant woman and stable and fall for elderly based on the data sets. The difference in this classifier the number of closest values are restricted to two successive data values rather than check-

Table 2. Percentage of data reduction compared with bench mark data

Dataset	Input Samples	Reduced Data Matrix	Compression Ratio
Toddler	3500	320[(10x4)*8]	90.86%
Pregnant Woman	3500	320[(10x4)*8]	90.86%
Elderly	3500	320[(10x4)*8]	90.86%
Clinical Gait Data	10500	1020	90.29%

ing all the data points in the domain. But the successive data values are defined as a strong closest values by introducing a safer threshold distance between the data point and the two different data sets and hence the no of iterations are reduced. This modification suggested, benefits the process by reducing time, and avoids repeated average calculations. The threshold is fixed by the experimental simulations with the knowledge gained by using real data in several repetitions.

6.2 IR-Threshold Classifier Algorithm

- Accumulate the values from feature extractor for both categories in all the three domains.
- Read the values S^i from the extracted data set where i is the current iteration within the domain {P1,.......,Pn} and {M1,.......Mn}.
- For all test data calculate the distance between the test data and the training data

  $d1 = Pi - x$ where x is the test data in the category $\{s, N, S\}$

  Similarly,

  $d2 = Mi - y$ where y is the test data in the category $\{D, C, F\}$.
- Sort the values based on the Distance d_i .
- Compare d1 and d2.If $d1 < d2$ loop,$P_i \in x$ then increment token X^T by 1,$X^T = X^T + \mathbf{1}$, else $M_i \in y$, increment token Y^T by 1, $Y^T = Y^T + \mathbf{1}$.

  Set δ as threshold ,

  $X^T \leq \delta$ *where* $P_i \in x$

  Set δ as threshold

  $Y^T \geq \delta$ *where* $M_i \in y$
- Use the majority of the distinguishing values as prediction value to calculate Accuracy.

7. Results

The reduced feature extracted dataset from Segmented Pigeon Hole Feature Extraction is fed to the IR threshold classifier which classifies the data set into fall and normal category. The classifier classifies based on the threshold factor of 0.6. The threshold factor is chosen based on the analysis done on various subjects taken during Fall and normal. The simulation results are taken from MATLAB and shown below in Figure 8, Figure 9 and Figure 10.

The evaluation of one to one pigeonholes was done for all the groups of the data matrix for all ten trials. The group of electrodes 9, 10, 11 and 12 in case of Toddler, electrodes 7, 8, 9 and 10 for pregnant woman and 9, 10, 11 and 12 in case of elderly seems to be constantly producing maximum differences for both the categories in all the

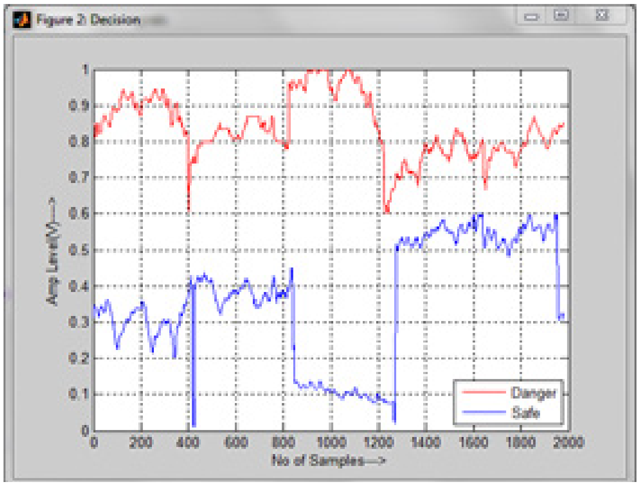

Figure 8. Classification of safe and danger category of toddler

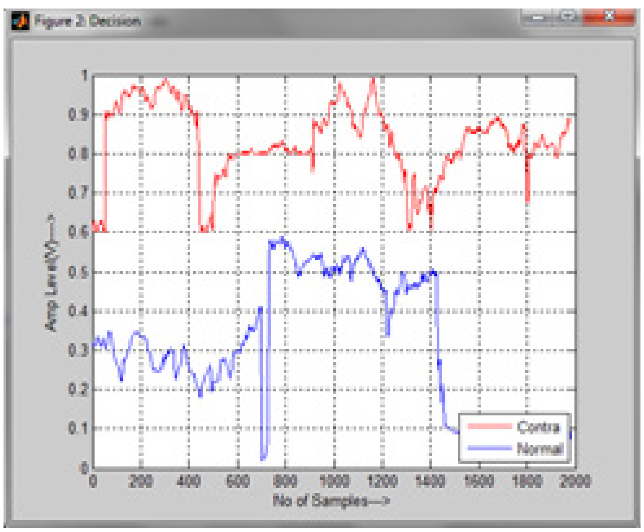

Figure 9. Classification of normal and contra category of pregnant woman using IR threshold classifier for subject 1.

three domains. This is due to the position of the electrodes positioned on the body of all three different type of subjects produced considerable differences compared to the other electrodes. The results shown in Table 3 shows the accuracy of IR threshold classifier which reduces the execution time and computing complexity to a significant rate, that is preferable for the application which require fast response.

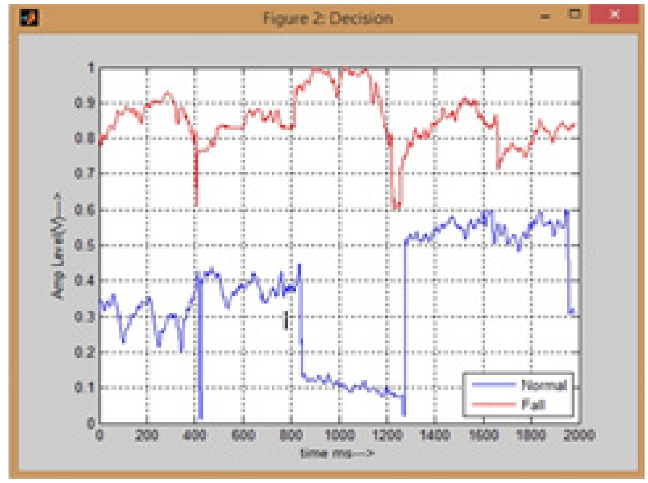

Figure 10. Classification of stable and fall category of elderly using IR threshold classifier for subject 1.

Table 3. Classification based on IR Threshold

Signals	Subjects	IR Threshold
Normal	1	10/10
Fall	1	10/9
Normal	2	10/9
Fall	2	10/8
Normal	10Avg	100/91
Fall	10 Avg	100/90

8. Conclusion

In this paper, a classification for the Toddler, pregnant woman and elderly using segmented pigeon hole technique and IR threshold classification that is trained to detect fall in the simulated elderly fall data sets. The system classifies the datasets into fall and normal category. Initially data is collected from 14 electrodes and then it is optimized into fewer four electrodes based on Segmented pigeon hole technique and then lesser data sets is classified using IR Threshold classifier. This is to recommend the best reduced set of data by means of reduced electrodes on the monitoring system to pick up the most predominant electrodes to increase the classification accuracy as well as to reduce the cost and size of signal data matrix to decrease the time of response. Similarly the classification results based on IR Threshold was done with the first group of electrodes and is listed in Table 3. Here too the first two subjects and the average of 10 subjects are depicted for space constraints. The experiment was conducted with the help of 5 subjects with 10 trials for each.

9. References

1. Roweis ST, Saul LK. Nonlinear dimensionality reduction by lo-cally linear embedding. Science. 2000; 290(5500): 2323–26.
2. Shao L, Seed L, Mubashir M. A survey on fall detection: Prin-ciples and approaches. Neuro Computing. 2013; 100:144–52.
3. Li B, Wang J, Simon Sherratt R, Lee S, Zhang Z. Enhanced fall detection system for elderly person monitoring using consumer home networks. IEEE Transactions on Consumer Elec-tronics. 2014; 60(1):23–9.
4. Naqvi SM, Rhuma A, Yu M, Wang L. A posture recognition-based fall detection system for monitoring an elderly person in a smart home environment. IEEE Transactions on Infor-mation Technology in Biomedi-cine. 2012; 16(6):1274–86.
5. Ho KC, Popescu M, Li Y. A microphone array system for automatic fall detection. IEEE Transactions on Biomedical En-gineering. 2012; 59(2):1291–301.
6. Li Y, Rantz M, Popescu M, Sku-bic M. An acoustic fall detector system that uses sound height information to reduce the false alarm rate. Proc 30th Int IEEE Eng in Medicine and Biol Soc Conference; 2008. p. 4628–31.
7. Jiang P, Jiang W, Winkley J. Verity: An ambient assisted living platform. IEEE Transactions on Consumer Electronics. 2012; 58(2):364–73.
8. Vaidehi K, Subashini TS. Breast tissue characterization using combined K-NN Classifier. In-dian Journal of Science and Technology. 2015 Jan; 8(1). DOI: 10.17485/ijst/2015/v8i1/52818.
9. Jayasri T, Hemalatha M. Catego-rization of respiratory signal using ANN and SVM based on Feature Extraction Algorithm. Indian Journal of Science and Technology. 2013 Sep; 6(9). DOI: 10.17485/ijst/2013/v6i9/37144.
10. Oliver AS, Samraj A, Ma-heswari N. Fuzzy ARTMAP based classification feature for danger and safety zone pre-diction for toddlers using wearable electrodes. Proceeding of IEEE Internaional Conference on High Performance Green Computing. ICGHPC'13; 2013. p. 1–6.
11. Oliver AS, Maheswari, Andrews S. Stable and critical gesture recognition in children and pregnant women by SVM clas-sification with FFT features of signals from wearable attires. Research Journal of Applied Sciences, Engineering and Technology. 2014; 7(23):4917–26.
12. Rhuma A, Yu M, Naqvi SMR, Wang L. An online one class support vector machine-based person-specific fall detection system for monitoring an elderly individual in a room environment. IEEE Journal of Biomedical and Health Informatics. 2013; 17(6):1002–14.
13. Xuan D, Dai J, Bai X, Shen Z, Yang Z. Mobile phone-based pervasive fall detection. Journal of Personal Ubiquots Computting. 2010; 14(7):633–43.