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 received 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.
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 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 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 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 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 analyzes 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 ambient based techniques more often than not depend with respect to weight sensors, acoustic sensors or infrared movement sensors implemented around overseers’ home. 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 parenchyma locale. K-NN with three diverse separation measurements specifically Euclidean, Cosine, City-block and its mix is utilized for arrangement. The extracted 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.8

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 intervals. 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\textsuperscript{10,11}.

3.1.2 Pregnant Women
An arrangement of 14 electrodes settled on the wearable slip belt of the subjects were utilized to record the mid-region development signs and estimations were taken for 5000 milliseconds (5 seconds) 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 1024 Hz, 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\textsuperscript{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\textsuperscript{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.

![System Architecture Diagram](image-url)
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\cite{12}. The systems classify the data sets into two classes that are safe and danger for toddler, normal and Contra for Pregnant woman 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\cite{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\cite{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
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 \( m \in DM1 \) and \( n \in DM1 \)
where \( m = 10 \) and \( n = 4 \) and \( n \leq i \geq m \)

For each partitioned DM2 let \( m \in DM2 \) and \( n \in DM2 \)
where \( m = 10 \) and \( n = 4 \) and \( n \leq i \geq m \)

Each Partition is represented as Pigeon hole \( \sum_{i=1}^{n} PH_i \)
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 \( \sum_{i=1}^{n} PH_i \)
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 \( m \in DM_i \) \&\& \( n \in DM_i \)
where \( m = 10 \) and \( n = 4 \) and \( n \leq i \geq m \)

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

For each Partition \( \sum_{i=1}^{n} SPH_i \)
in abnormal activity

do

Compute mean vector \( x \) and \( y \)

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

compute variance of \( x \) and \( y \)

\[
\text{variance}(dm): \ \sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (dm_i)^2 - m^2
\]

compute variance of \( x \) and \( y \)

\[
\text{skewness}(dm): \ \psi = \frac{1}{N} \sum_{i=1}^{N} (dm_i)^3 - m^3
\]

then

Compute the distance between the features \( x \) and \( y \)

is calculated as

\[
s_m = \sum_{i=1}^{n} (x_i - y_i)
\]

\[
s_v = \sum_{i=1}^{n} (x_i + y_i)
\]

\[
s_x = \sum_{i=1}^{n} (x_i - y_i)
\]

. Calculate first four

\[
C_{i,xy} = \max(sum(s_m + s_v + s_x))
\]

Figure 5. Data reduction using SPH technique of subject 1 of toddler.
The electrodes 9, 10, 11 and 12 i.e., electrodes placed in left foot, right thigh, right knee and right foot show 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 dataset.

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.

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-
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 \( \{P_1, \ldots, P_n\} \) and \( \{M_1, \ldots, M_n\} \).
- For all test data calculate the distance between the test data and the training data
  \[ d_1 = P_i - x \] where \( x \) is the test data in the category \( \{s, N, S\} \).
  Similarly,
  \[ d_2 = M_i - y \] where \( y \) is the test data in the category \( \{D, C, F\} \).
- Sort the values based on the Distance \( d_1 \).
- Compare \( d_1 \) and \( d_2 \). If \( d_1 < d_2 \) then increment token \( X^T \) by 1, \( X^T = X^T + 1 \), else \( M_i \in y \), increment token \( Y^T \) by 1, \( Y^T = Y^T + 1 \).

Set threshold as

- \( X^T \leq \delta \) where \( P_i \in x \)
- \( Y^T \geq \delta \) 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

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    | 10500         | 1020                | 90.29%            |
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.

### 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    | 10Avg    | 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.

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