International Journal of Modern Agriculture
ISSN: 2305-7246
Volume 10 Issue 2, Month 2021

STABLE AND FALL RECOGNITION IN ELDERLY USING PIGEON HOLE DATA REDUCTION AND OPTIMIZATION TECHNIQUE AND MODIFIED K-NN CLASSIFIER

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Abstract—Remote health care monitoring is a technology which enables monitoring of person outside of conventional clinical settings i.e. in the home, which may increase access to care and decrease healthcare delivery costs. UNICEF says about 50% Fall accident in the elderly person is a risk and it is increasing. Statistics indicates that one out of three people over the age of 65 will fall. Various fall detection solutions have been proposed to detect fall. In this paper, it is proposed that the data from different subjects are classified into safe and danger using a best computational classifier which can be given as an input to an automated device. The classifier is to classify the simulated data sets of elderly fall. The dataset of simulated for all the types of subjects of elderly fall was provided by a wearable dry electrode attire which is tied on the abdomen for elderly. Using a machine learning algorithm, the algorithm classifies the all the data sets into Stable and Fall for elderly . Based on the classification, it can notify the care taker or remote assistance about the them whether they are in Safe condition or not.

Keywords — Wearable Electrodes,Feature Extraction, Machine Learning Algorithm, Fall And Normal Category, Pigeon Hole, K-NN.

1. INTRODUCTION

Falls are measured as a main risk in health issues among elderly people which causes increases in the mortality, morbidity rate and also it is a source of loss in autonomy now it lead to a significant impacts on national health system. According to WHO [18] 40% of people above 65 of age tend to fall at least once a year. This fall causes serious injuries and hospitalization rate to increases by an average of 2% until 2030[6].

The fear of falling among elders have been increasing so the confidence level of living independent is Decreasing. Records show about 3% of fallers lie without an external support and are unable to get up by themselves. Hence automatic notification to their family or caregivers after fall will be a helpful to provide an immediate medical. After fall injuries include broken bones, abrasions to the skin and soft tissue damage [12][13]. Helping people to provide a better life has many social benefits.

The development of wireless network and sensing technologies provide the realization of context awareness in wireless body area network (WBAN). These sensors provide a central device to collect raw data from the human body. Fall detection would reduce the time between fall and arrival of medical help [3] this is realized by an automatic fall detection system through a Personal Emergency Response. System (PERS). The process of detecting and preventing fall is a challenging task.They are different fall detection approaches such as smart clothing, smartphones, smart watches and activity trackers. Recent systematic reviews highlights many proposed technology including the indication of false alarms and their cost effectiveness [4] these approaches uses of additive sensors such as a accelerometers, gyroscopes or ambient sensors. Previous techniques also include ADL as falling down with both legs straight or with knee flexion [2][1] This fear may cause them to limit their activities, which lead to reduced mobility and loss of physical fitness and in turn increase their actual risk of falling. Every parent knows how hard it is to protect a child from injuries related to falling. When a baby first learns to walk, or when plays in the room preventing falls requires constant supervision. It is very important for women to receive health care before and during pregnancy to decrease he risk of pregnancy complications. Every 10 minutes a woman dies in India from pregnancy and complications of child birth. In order to reduce threeall these such mishaps from occurring, various detection solution have been proposed earlier which cannot be afforded by a common man. In this paper, the concept of data mining and machine learning concepts are used to propose a cost effective technique using wearable electrodes worn to monitor and to send safe and danger signals to the care taker. The proposed approach is to collect data from toddler, pregnant woman and elderly subjects and to classify the simulated datasets. After classifying the data sets it can be the input to a device which can alarm the care taker. Data mining [22] is an interdisciplinary subfield of computer science used to mine patterns from a large data set. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Machine learning is scientific study that deals with the construction and study of the algorithm that can learn from the provide data. The rest of the paper is organized as follows: Section II details related works. Section III describes the system architecture. Section IV explains the fall detection system in detail. Section V illustrates on the techniques. Section VI Conclusions of the paper.

2. RELATED WORKS

Fall detection systems are based on sensors that are located in the environment an example is the Context Aware System (CAS). This system is integrated with vision based and ambient based systems that includes cameras and microphones. . Like the wearable FDS the CAS architecture easily provides the communication interface and the monitoring process is carried out in a low cost. Similarly the smartphone-based architecture benefits from the commercial device that integrates with an inertial measurement unit (IMU) it supports multi interface wireless communication. They considered the mobility datasets that obtained wearable IMU that include falls from the monitored users. The collected data sets are from the experimental subjects from mobility sensors mainly accelerometers that is attached to human body. The samples were measured by wearing these devices during the daily life.

In the machine learning technique classification is the process to identify the sub-populations that belongs to the training dataset that is provided by the user. The classification algorithm classifies the activities of the elderly people using height, velocity and fall movements. By detecting those movements the extract position of the elderly fall is found and the data is run through the machine learning classification algorithms to confirm fall. The various classification algorithm are support vector machine (SVM), K Nearest Neighbor (KNN) , Navies Bayes and Decision trees. In SVM the human joint measurements has been utilized that provided good performance [8].

The activities of daily living and the fall detection algorithms developed in the existing systems are very efficient and it was implemented using the microcontroller unit ,random access memory and clock speed. Fig 1 shows the Fall detection approach.

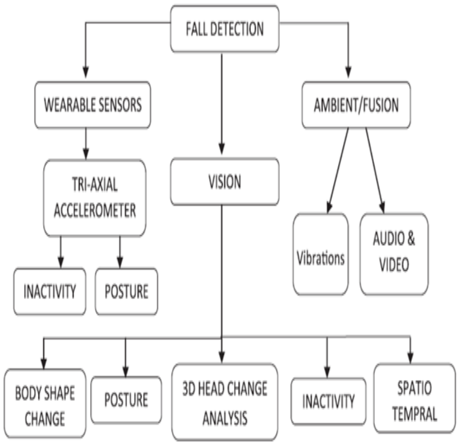

Fig1: Fall detection approach

Elderly Fall

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 slip belts 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 A.The Data acquired using 14 electrodes from

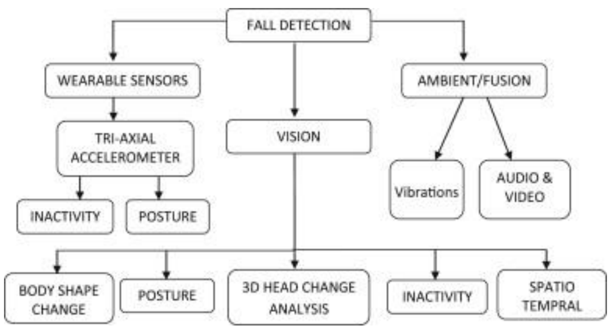

Fig 2 Classification of Fall Detection methods

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.[23][24]

3System Architecture

The proposed system is a wearable based system. The system architecture comprise of wearable attire, automated device and triggering device. The Fig 3 illustrates the system architecture diagram.

3.1. 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.

3.2. Automated Device

The automated device receives the signals reading from the transmitter. The automated device receives reading for every 5s. The device coverts the analog data into digital. The data is then analyzed reduced and extracted Then the data is fed to a classifier and pattern recognition device that analyses the signal data received from the wearable attire.

3.3. 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 all three experiments Then upon identifying any abnormalities it notifies a triggering device.

3.4Triggering 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. This device can be developed as a future enhancement of the work

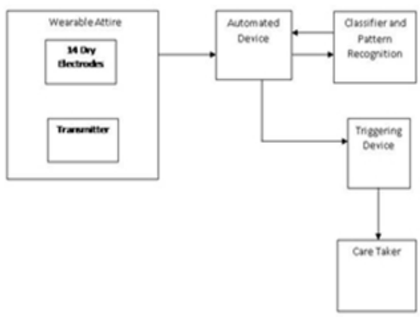

Fig 3 System Architecture Diagram

4. SYSTEM ANALYSIS

The proposed system comprised of an automated detection system. Wearable attire is a belt in abdomen of the elderly and pregnant woman and an attire for toddlersused 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 person. 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. 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 as shown in Fig 4.

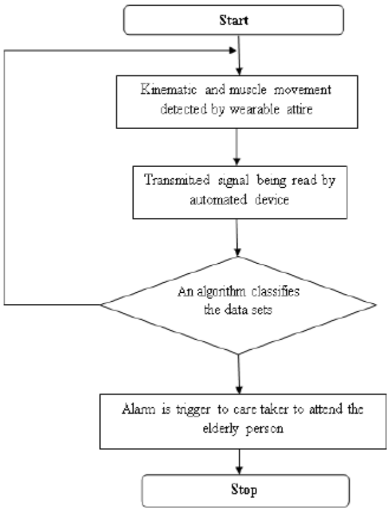

Fig 4 System Analysis Flow Chart

5SYSTEM 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 dimension reduction is the process of reducing the number of random variables under consideration[*]Feature extraction transforms the data in the high-dimensional space to a space of fewer dimensions. 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.

5.1 PIGEON HOLE OPTIMIZATION ALGORITHM

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[22].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 plotof 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

The sampling and 4 to 5 second duration is not precisely uniform in the data acquisition due to variable time. 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.

Algorithm: Pigeon Hole Optimization Algorithm

Input : Data Signal Matrix
Output :Reduced data representation, Difference value between two test classes

Begin

Segment or Partition the data signal matrix of Stable as DM1 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

$\sum_{i=1}^{n} PHi$for {s,N,S}

where s=Safe,N=Normal and S=Stable of all the three domains

Each Partition is represented as Pigeon hole

$\sum_{j=1}^{n} PHj$ for {D,C,F}

where D=Danger,C=Contra and F=Fall of all the three domains

Compute mean vector x for each pigeon holes in safe category and also y compute mean vector for each pigeon holes in danger category for toddler.

$$x = \sum_{i=1}^{N} PHi/N$$

$$y = \sum_{i=1}^{N} PHj/N$$

International Journal of Modern Agriculture
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Covariance of the matrix is calculated by

$$C = \sum_{i=1}^{n} \frac{(Xi - x)(Yi - y)}{n - 1}$$

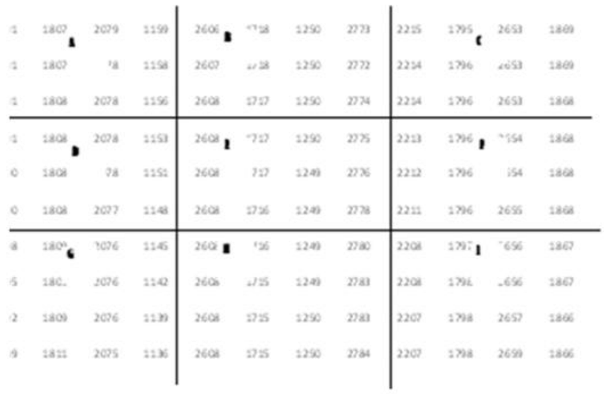
where x and y denoting the means of X and Y, respectively.

Compute singular values and subtract the values found in stable data with the values of fall

$$S = \sum_{i=1}^{n} (x - y)$$

Compare the values and calculate the distance which produce maximum difference between DM1 of safe and DM2 of danger

Pigeon holes PHi & PHj which gives maximum difference is taken for and the electrodes which contribute are taken for further classification process.



1	1807	2079	1159	2606	[illegible]	1250	2773	2215	1795	2653	1869
1	1807	[illegible]	1158	2607	[illegible]	1250	2772	2214	1796	[illegible]	1869
1	1808	2078	1156	2608	1717	1250	2774	2214	1796	2653	1868
1	1808	2078	1153	2608	[illegible]	1250	2775	2213	1796	[illegible]	1868
0	1808	[illegible]	1151	2608	[illegible]	1249	2776	2212	1796	[illegible]	1868
0	1808	2077	1148	2608	1716	1249	2778	2211	1796	2655	1868
8	[illegible]	[illegible]	1145	[illegible]	[illegible]	1249	2780	2208	[illegible]	[illegible]	1867
5	[illegible]	2076	1142	2606	[illegible]	1249	2783	2208	[illegible]	[illegible]	1867
2	1809	2076	1139	2608	1715	1250	2783	2207	1798	2657	1866
9	1811	2075	1136	2608	1715	1250	2784	2207	1798	2659	1866

Fig.5 Pigeon hole segmentation of datamatrix signal from 14 electrodes

The electrodes 9,10,11 and 12 i.e electrodes placed in left foot, rightthigh, right knee and right foot shows maximum difference. The pigeon holes(PHi) 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 pigeon hole optimization 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....24are 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.

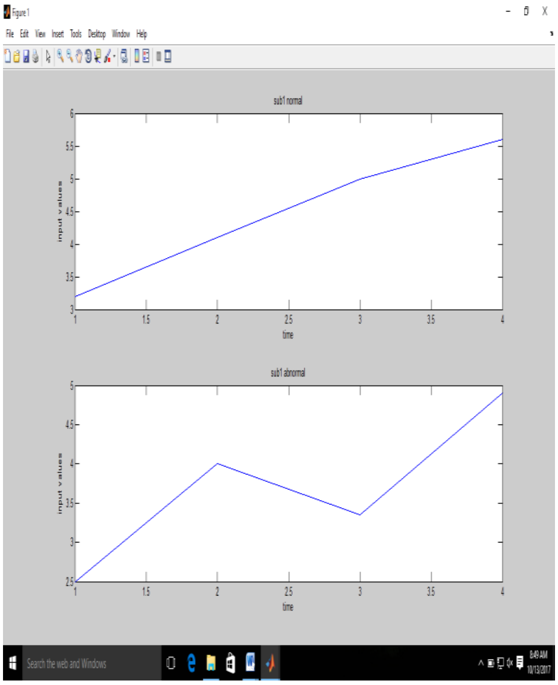


Fig 6. Optimization Algorithm of subject 1 of Elderly

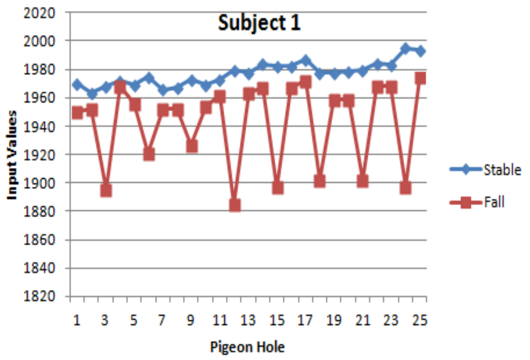


Figure 7 Data reduction Using Pigeon Hole

Due to Space constraints the output figure is restricted to subject 1 .

k-NN CLASSIFIER(Modified)

k-NN is one of the machine learning algorithm. KNN is a method for classifying objects based on closest sample values of data in the feature space. Two different set of input data is

classified by a majority vote of its neighbors. K is always a positive integer. The neighbors are taken from a two set of input data for which the correct classification is found. The algorithm proposed and used here is the modified k-NN 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 provided as the k-NN. The difference in this modified k-NN is the number of nearest neighbors are restricted to two successive neighbors rather than checking all the data points in the domain. But the successive neighbors are defined as a strong neighbors by introducing a safer threshold distance between the data point and the two different data sets. This modification suggested by us, benefits the process by reduced 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.
Algorithm: k-NN(modified)
Input: Reduced data from pigeon hole algorithm,
Output: classified data

BEGIN

Represent the reduced data matrix as D

Initialize Centre points and classes x & y

Initialize a variable token as X^T and Y^T

$x_i = 0, y_i = 0$

LOOP

Read the member from the space M

Calculate the distance

$d1 = Mi - x$

$$d1(Mi, x) = \sqrt{\sum_{M=1}^{D} (x_M - x_i)^2}$$

$= \sqrt{||x_M^2||} + \sqrt{||xi||^2} - \sqrt{2x_M}xi$

$d2 = Mi - y$

$$d2(Mi, y) = \sqrt{\sum_{M=1}^{D} (y_M - y_i)^2}$$

$= \sqrt{||y_M^2||} + \sqrt{||yi||^2} - \sqrt{2y_M}yi$

if $d1 > d2$

loop

$M_i \rightarrow x_i$ where x_i is the member of x

else

$M_i \rightarrow y_i$ where y_i is the member of y

increment token X^T by 1

$X^T = X^T + 1$

increment token Y^T by 1

$Y^T = Y^T + 1$

end loop

Set $\delta = 0.6\ where\ \delta\ is\ threshold$

if $(X^T \geq \delta)\ then$

$M\ belongs\ to\ x$

if $(Y^T \geq \delta)\ then$

$M\ belongs\ to\ y$

else

REPEAT LOOP

6 EXPERIMENTAL RESULTS AND DISCUSSION

The reduced feature extracted dataset from Pigeon Hole algorithm is fed to the k-NN classifier as well as the modified k-NN which classi

Fig 7. Stable and fall graph

fies the data set into different categories. 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 all the criteria. The simulation results are taken from MATLAB and shown below.

Similarly the classification results based on k-NN was done with the first group of electrodes 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 ten subjects with 10 trials for each.

The evaluation of one to one pigeonholes was done for all the groups of the data matrix for all ten trials. The group of electrodes9,10,11&12 in elderly seems to be constantly producing maximum differences for both the categories in all the 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 which makes no difference in accuracy in the case of k-NN and modified k-NN, but the time taken by the modified k-NN reduces the execution time and computing complexity to a significant rate, that is preferable for the application which require fast response.

CONCLUSION

In this paper, a classification for the elderly using pigeon hole optimization Algorithms and modified k-NN 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 electrodes based on pigeon hole optimization technique and then lesser data sets is classified using k-NN and modified k-NN 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.

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	Electrode 1	**Electrode 2**	**Electrode 3**	**Electrode 4**	**Electrode 5**	**Electrode 6**	**Electrode 7**	**Electrode 8**	**Electrode 9**	**Electrode 10**	**Electrode 11**	**Electrode 12**	**Electrode 13**	**Electrode 14**
Elderly	Left up-per arm	Left middle arm	Left lower arm	Lower hip back	Lower hip front	Right up-per arm	Right middle arm	Right lower arm	Left up-per leg	Left knee	Left foot	Right up-per thigh	Right knee	Right foot

Table A Electrode positions