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Practical Fall Detection System using Vision and Wearable sensors

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Abstract*: Fall detection is an important and challenging research problem in healthcare domain. The fall detection system required to operate and give true alert in real time. Many of the existing approaches generates false fall alert which again causes inconvenience for the end users. Hence, there is a need to have robust and accurate fall detection approach with low latency in decision making. In this work, we have proposed and evaluated three different approaches of fall detection system based on a wireless accelerometer based embedded system, RGB Image processing based Software modelling approach and Kinect based depth processing approach. These proposed approaches try to improve on the mentioned drawbacks until we obtain a robust, running in real-time system with high accuracy and low processing time. In all of the demonstrated methods, we do not require any knowledge of the scene and computationally intensive classifiers. The accelerometer based embedded system consists of economic components and is easy to setup. RGB Image processing based Software modelling is simulated on MATLAB have been extensively researched and implemented in real-time. Kinect based depth based techniques are the most recent advancement on the issue and have resolved many discrepancies of the previous methods. The performance of each method is compared against each other. It is shown that our Kinect based depth processing provides promising accuracy of 94% which is better than the other approaches while simultaneously working in real time of 30 frames/second.

Keywords: Kinect, RGB, MATLAB, Depth Image.

I. INTRODUCTION

Fall is characterized as an occasion where, brings about an individual stopping unintentionally on the ground or floor or other lower level. Fall related wounds might be lethal or non-deadly. Falls are the subsequent driving reason for coincidental or unexpected damage passing around the world. Every year an expected 646,000 people kick the bucket from falls all-around of which over 80% are in low-and center pay nations. Grown-ups more established than 65 years old endure the best number of deadly falls. Practically 37.3 million individuals falls which are extreme enough to require restorative consideration happen every year [1].This paper presents three systems regarding detection of falls and compares their accuracy in real time environment.

The first system makes use of economical electronic modules for the detection of human motion. This falls in the category of wearable devices. The wearable has the ability of detecting a fall utilizing accelerometer associated with an Arduino microcontroller. The calculation quantifies the speeding up on 3-axis accelerometer and the angular position of the item [2]-[4].It consists of a series of checkpoints to eliminate other routine activities from an actual fall. Once a fall has been detected, a Bluetooth module connected to the Arduino sends an alert to any device connected to the module. The experimental results show that average fall accuracy is 83%.

The second system is based on a simulation model implemented in MATLAB R2017a. This system requires the use of one or many cameras to detect falls for the human population using image analysis. Using computer vision algorithms, the system detects motion of a person without any physical intrusion as that of wearables. The object is highlighted using image extraction algorithms and motion is tracked [5]. Further, thresholds are set for the orientation of the body and speed of motion; which when crossed send an alert to indicate a person has fallen. The experimental results show that accuracy is very high but processing time is not feasible for real-time applications.

Vision depth image systems are the key to achieving high accuracy with low processing time algorithms for fall detection. They use infrared sensors to track and examinations human movement [6]. Depth picture examination has a favorable position with respect to protection and area following of the individual since the information acquired has no facial features nor does area attribute. A very popular and affordable depth camera is Microsoft Kinect. Depth information is obtained from the Infrared camera of the Kinect to generate a skeleton of the person for motion tracking. This system achieves the highest accuracy of 94%.

II. RELATED WORK

In this segment, we expand on the most important work done to recognize falls. Approaches to this problem over the years usually fall in one of these three categories: wearables, vision based and depth based. In this paper, we test each method for accuracy as well as computational time to determine the best method for real-time applications. Most of the wearables use an accelerometer for fall detection as it is extremely reliable and easy to use. The problem is distinguishing other human activities from a fall as the device provides only one type of input-acceleration [3].

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Hence to distinguish a fall, Chen J [7] proposes a system which calculates orientation of the person simultaneously with impacts within time thresholds i.e. a series of checkpoints which need to be crossed to detect a fall. A similar approach has been taken up by [8], here the authors place the accelerometer on the person's pelvis.

The algorithm takes into account various scenarios such as stand_still, sit_to_stand, stand_ to_ sit, walking, walking_backwards, stoop_up, jump and lie_ on_ the_bed. Within these scenarios, fall detection runs in parallel.

In the work [9], it was proposed a computerized checking framework dependent on picture preparing progressively; this framework distinguishes the substance of an individual in a given territory, gathers information, for example, the speed of movement of the individual, and decides if the individual has endured a fall; a caution is activated quickly upon the recognition of a fall. A widely known parameter for fall detection is *inactivity detection:* a person will become inactive if he becomes unconscious due to injury. Nait-Charif, H., & McKenna [10] use omni-cameras to track the person and obtain motion traces of the person .Based on these motion traces, each activity is classified into a subgroup and inactivity is one of these parameters.

Depth based systems are the newest approach to fall detection and although there are many systems available, Mastorakis, G. and Makris, D [11] and Stone, E. E.,and Skubic, M. [12] have proposed a high accuracy and reliable 3D depth system. They have used Microsoft kinect camera along with OpenNI to analyse the depth information and generate a 3D bounding box. Using only 3 parameters: height, width and depth, they analyse each frame and create the bounding box for the new values. They then calculate rate of change of these parameters to detect a fall.

III. METHODOLOGY

In this area, we will depict our strategies for fall recognition.

A. Accelerometer based wearable embedded system

The prototype consisting of Arduino Uno Microcontroller, ADXL335 accelerometer and HC-06 Bluetooth Module as shown in Fig.1. The modules have been connected together using jumper wires. On the smartphone end, many applications are available for Bluetooth connectivity to HC-06. For this experiment, we have used *Serial Bluetooth Terminal* to receive any alerts from the wearable device.

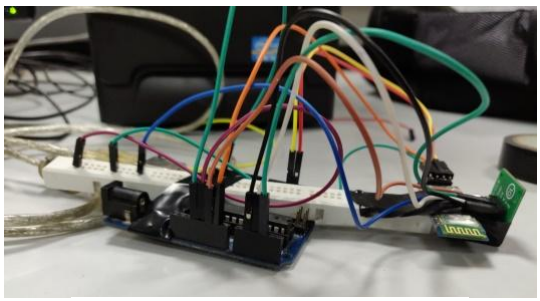

Fig.1. Wearable Embedded System

This system consists of two main components. The first is the wearable device, accelerometer (ADXL335 module) is connected to an Arduino Uno microcontroller and is powered by a battery or power bank. The aim is to make this a standalone system without the need of charging. A Bluetooth module (HC-06) is also connected to the Arduino as a mode of communication.

The second component is a mobile application running on the receiver's smartphone. The phone should have Bluetooth capability and can connect easily to HC-06. The first step is to connect to the wearable, the microcontroller runs the fall detection algorithm and sends an alert to the smartphone if a fall is detected. Assigning simple thresholds will not do the job, the net acceleration, pitch and roll is calculated using (1), (2) and (3) as given below

$$A_{net} = \sqrt{Ax^2 + Ay^2 + Az^2} \quad (1)$$

$$\text{Pitch} = \tan^{-1}\frac{Ax}{\sqrt{Ax^2+Ay^2}} \quad (2)$$

$$\text{Roll} = \tan^{-1}\frac{Ay}{\sqrt{Ax^2+Az^2}} \quad (3)$$

The flow chart of the proposed methodology is shown in Fig.2.

Stage 1: There will be a fall in the worth when the fall begins. Along these lines if the worth goes underneath a particular edge (for this situation, 0.8g) it passes the main checkpoint.

Stage 2: Following the fall, the client has effect with the ground or surface. A sharp spike in the net readings portrays this. For our motivations, we net speeding up on fall as more noteworthy than 1g. The time slack between the checkpoints must be no more noteworthy than 2 seconds.

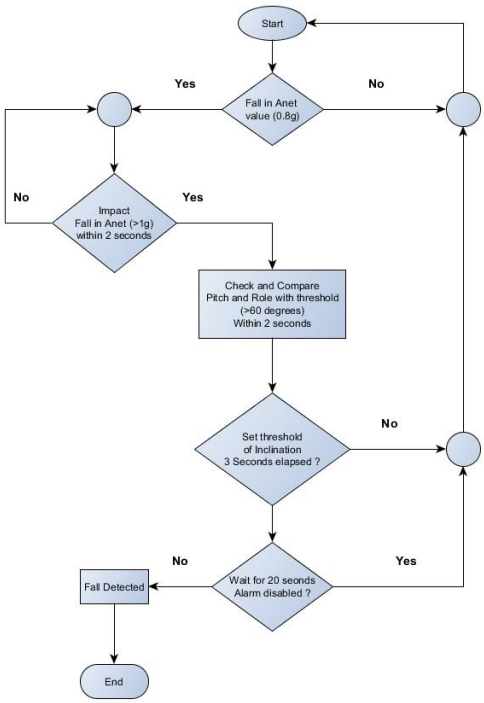

Fig.2. Flow chart of wearable embedded system

Step 3: Stage 3: The pitch and move of the client is checked and contrasted and a predefined limit (For this situation, more noteworthy than 60 degrees). The time slack between checkpoint 2 and 3 must be exceptionally little – in the request for milliseconds.

Stage 4: We presently check for a time of 3 seconds whether the client gets up, by setting a limit on tendency.

In the event that 3 seconds have slipped by, we can expect a fall has been detected. Stage 5: We presently hang tight for a time of 20 seconds for the client to debilitate the alarm, if there should arise an occurrence of bogus alert. In the event that 20 seconds have slipped by, we affirm the fall and alarm is sent by means of Bluetooth.

B. RGB Image processing based Software modelling

The research work [13] uses Motion History Images (MHI) which is based on large movement of the person. The MHI is an image where the pixel intensity represents the newness of motion in an image sequence, and therefore gives the most recent movement of a person during an action. To extract the moving person in the image, we use a background subtraction method described in article [14] which gives good results on image sequences with shadows, highlights and high image compression. The person is then approximated by an ellipse using moments [15]. The parameters to characterize a circle are its Center (x, y), direction Θ and length of major and minor hub. For a nonstop picture f (x, y), the minutes are given beneath in (4)

$$m_{pq} = \iint_{-\infty}^{+\infty} x^p y^q f(x,y)\,dxdy \tag{4}$$

The Center of the circle is found by the directions of Center of mass and first request minutes as in (5),

$$x_1 = m_{10}/m_{00}; y_1 = m_{01}/m_{00} \tag{5}$$

The central moments of order p, q is given by (6),

$$\mu_{pq} = \iint_{-\infty}^{+\infty} (x - x_1)^p (y - y_1)^q f(x,y)\,dxdy \tag{6}$$

The edge between the significant pivot of the individual and the flat hub x gives the direction of the oval, and can be registered with the focal snapshots of second request (7)

$$\Theta = \frac{1}{2}\tan^{-1}\frac{2\mu_{11}}{\mu_{20}-\mu_{02}} \tag{7}$$

The approximated circle gives us data about the shape and direction of the individual in the picture. To eliminate a fall from other daily activities which also involve large motions, analysis is done on the proportions of the approximated ellipse and the orientation of the person. The orientation standard deviation σ_Θ is calculated to be high if the person falls perpendicular to camera axis and will be low for walking. Ratio standard deviation σ_ρ will be high if the person falls parallel to the camera axis but will be low for walking.
σ_θ and σ_ρ are figured for a 1s length. We assume that an enormous movement is a fall if σ_θ is higher than 15 degrees or if σ_ρ is higher than 0.9. These edges on σ_θ and σ_ρ are adequate to be uncaring toward little oval varieties because of a boisterous direction. A final checkpoint is crossed if the person becomes immobilized after the fall due to some injury. When a fall is recognized, we screen the state of the oval to check for any abrupt changes. If the ellipse shape and orientation remain unchanged, then we confirm the fall and appropriate alarms are triggered. An unmoving shape is characterized by $\sigma_a < 2$ pixels, $\sigma_b < 2$ pixels and $\sigma_\theta < 15$ degrees; where σ_a, σ_b are the standard deviations of major and minor hub of the circle.

C. Kinect based depth processing approach

Authors of [12] make use of OpenNI which is an important development tool for Kinect. This software is provided by Prime_Sense and can make use of the depth information provided by Kinect. OpenNI usually requires Microsoft Visual Studio to write or edit codes, which is a heavy software and requires much installation procedures before one can start. In our strategy we use Processing 3.0, an open-source programming made by Ben Fry and Casey Reas and has been utilized as a product sketchbook and a language for figuring out how to code inside the setting of the visual expressions.
Within Processing 3, Kinect libraries are easily installed which enables us to analyse depth information of the scene. Using the depth image we highlight our object and use background subtraction like previous methods. This removes all unnecessary data from the image and reduces computation time. Further to it, for each edge, the depth picture is handled by the Kinect run-time to change over into skeleton information. Skeleton information contains 3D places of every skeleton joint is put away as (x, y, z) features. Not at all like depth space, are skeleton space features communicated in meters. The x, y, and z-axis of the body points of the depth sensor as show in Fig.3.

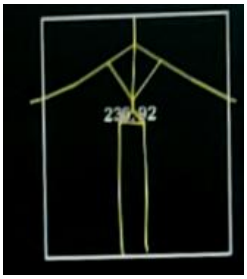

Fig.3. Skeletal Depth Image

Unlike [16], our algorithm does not require to calculate and use floor coordinates. Once the skeleton data is extracted and the joints generated, a 2D bounding box as shown in Fig.4. is created. It powerfully changes its size as indicated by position and direction of the body. The length and width of the box is continuously calculated, we define a variable known as rate of change of height which is calculates the first derivative of height.

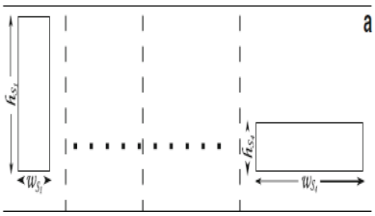

Fig.4. Two dimensional bounding box

Since a fall is a quick event, the change in height would be rapid and this would increase the value of the derivative. When this value exceeds a predefined- threshold, a fall may have occurred. The algorithm 1 is as given below:
SET Threshold T_{vh};
SET Boolean activity = false;
SET Threshold T_{ih};
while** run **do

```
    if ( V_h > T_vh ) then
        set activity = true;
    end if
    if ( activity == true and h < T_ih ) then

        if ( inactivity ) then
            set Fall Detected;
        end if
    end if
end while
```

Where the threshold is calculated based on (8)

$$V_h = \frac{h_i - h_{i-1}}{t_i - t_{i-1}} \quad (8)$$

A fall consistently finishes at an inertia state where no movement is distinguished (for example resting place). Subsequently, the fall finish is distinguished by checking the proper speed condition.

IV. RESULTS

A. Wearable embedded system

The experiment is conducted on 10 persons and each doing the action types of forwards, backwards (slip), sitting and object pickup (should not detect a fall). The accuracy of the system is reported in Table. I.

Table- I: Accuracy of wearable embedded system

Fall Type	No. of Falls	Falls Detected	Accuracy (%)
Forward	25	20	80
Reverse (Slip)	25	21	84
Sitting	25	18	72
Picking up Object	25	24	96

We also get the mobile alert notification in real time as shown in Fig.5.

Fig.5.Fall notification to user mobile

B. RGB software modelling approach

Our framework is intended to work with a solitary uncalibrated camera. As we want a cost effective system, we use the front camera of a laptop/ webcam with a USB port. The setback is processing each frame of real-time feed, live transmission from the camera to the software is not supported. Instead, the data from the camera is first stored and then processed. Fig.5.shows the output of the fall detection case.

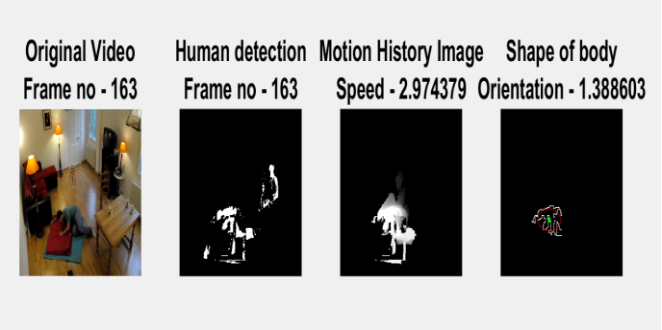

Fig.5. Fall Detection Process and Alert.

Experiment conducted on a predefined data- set containing 53 videos of which 50 were detected as fall. And the approach gives an accuracy of 94.33 s. However the computation time is not real time as it takes 1 to 2 seconds for each frame.

C. Kinect Depth Processing Approach

Experiment is performed with the help of 10 persons each doing the different action types and the accuracy of the system is evaluated.

Figures (6), (7), (8) and (9) shows the different depth images and its respective decision of fall and No fall cases.

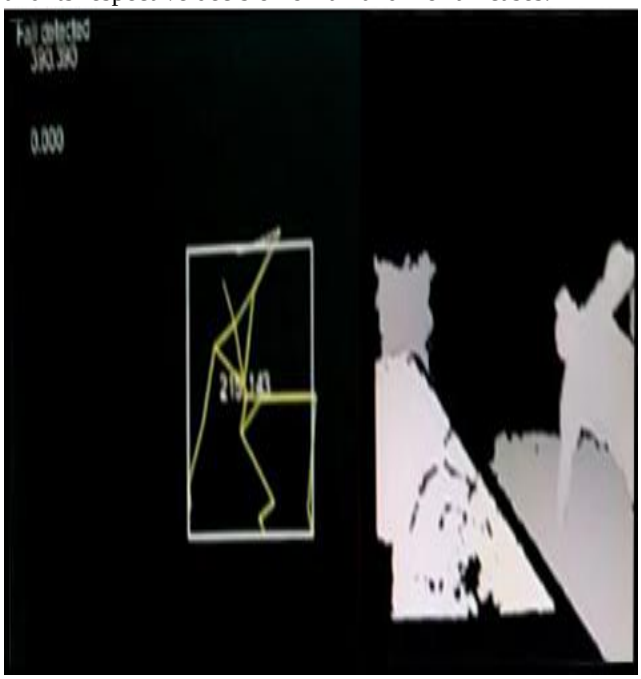

Fig.6. Forward Fall Detection

The accuracy of the system is reported in Table.II

Table- II: Accuracy of Kinect Depth Processing

Fall Type	No. of Falls	Falls Detected	Accuracy (%)
Forward	25	23	92
Reverse (Slip)	25	22	88
Sitting	25	24	96
Picking up Object	25	25	100

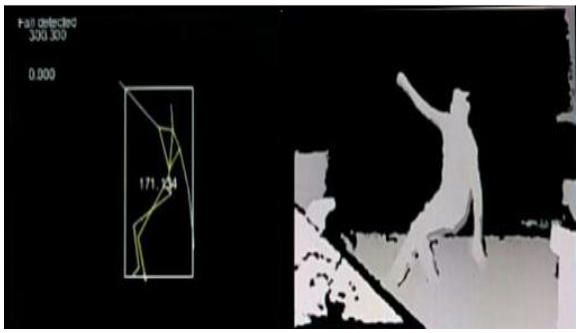

Fig. 7. Reverse Fall Detection

Fig.8 Sitting Fall State

Fig.9. Object Picking No Fall

V. CONCLUSION

We have demonstrated three techniques for fall detection that requires no pre-knowledge of the scene. Our goal was to compare the existing methods and try to improve the most feasible one. The wearable device proved to be quite sufficient for fall detection **(83%)**; the accuracy can definitely be improved with industrial level modules, further the person may forget to wear the device 24/7 and can sometimes be intrusive. A more robust system was researched and demonstrated on MATLAB that does not require any physical intrusion. Although the accuracy of the algorithm was high **(94.33%)**, it was not suitable for real-time applications due to processing time and also the issue of privacy of the person. Since the algorithm makes use of RGB images, the person's face as well as surroundings are available to unwanted eyes.

To tackle privacy issue and processing time, we move onto depth based techniques using Kinect and Processing 3.0. From the above results, we obtain a similar accuracy **(94%)** to that of RGB based algorithms without any lag in detection. A depth image does not show person's features and helps with privacy. Generating a skeleton easily tracks joint movement and orientation irrespective of the person's physical size. Our framework is quick, powerful and utilizes a modest sensor, accordingly, it very well may be effectively applied on an enormous scale for dependable fall identification. With its conventional application, our framework can be utilized in the all-inclusive community and furthermore contribute in supporting autonomous living of the old.

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