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RESEARCH ARTICLE

Enhanced Fall Detection for Seniors with Sensor Fusion and Optimized AI Techniques

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ABSTRACT

Senior citizens often prefer privacy and may live alone in secluded homes, making fall-related injuries a serious concern, especially during nighttime or in washrooms, where immediate assistance is unavailable. This study proposes an AI-based fall detection approach utilizing particle swarm optimization (PSO) to enhance the accuracy of a sensor fusion mechanism integrated with biomarkers for improved fall assessment. The PSO algorithm optimizes feature selection, refining sensor data interpretation to reduce false alarms while ensuring reliable detection. The analysis is conducted using MATLAB, demonstrating promising insights into the effectiveness of the proposed method in real-world elder care applications.

Keywords: Senior citizen care, Slip, Fall, Particle swarm, Sensor fusion.

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INTRODUCTION

Monitoring elders without hindering their privacy is an important part of research in the medical assistance world today. The reason is that too many elders are living alone and too many people are staying away from their parents. Kosa *et al*.[1] discuss intensive care medicine with robotics, but it is not possible with robotics that we can achieve full privacy of elderly senior citizens. Demographics predict that more elderly patients will need to be treated with fewer healthcare personnel, calling for innovations in ICU management. Xefteris *et al*.[2] have done an overall study on various types of possibilities in studying fall detection in elders. Several researchers have elaborated on the usage of particle swarm optimization and its advantages and limitations.[3-6] This work focuses on elderly care where monitoring elders efficiently is an important task as part of alerting the care takers immediately when some unforeseen incident occurs.

RESEARCH METHODOLOGY

Particle swarm optimization (PSO) is considered to be the mother of all naturally inspired algorithms, where birds flocking together decide the best direction for movement. The algorithm, as shown in Figure 1, starts with starting with an initial position of population and reaches the best solution, which is optimally the best. This logic of a naturally inspired algorithm is applied to fall detection in elders, where the initial position of the particle will decide the position of the individual. The updates to the position will indicate whether a fall has occurred or not. Fitness is an indication of the wellness of the individual. The lower or higher value of the fitness is very much dependent on the value of deviation in the coordinates of the elderly person from the original position, which is captured and analyzed by the program for evaluating the accuracy of the fall.

Simulation-Based analysis

Due to the challenges in acquiring large, ethically sound datasets of real-world fall events with corresponding biomarker data, this study utilized a simulated dataset generated using Python code that generates the coordinates randomly in space. Some information about the way this was done is as follows:

Fall Indicators

The fall indication was done on the following basis:

- *Distance from Center*

If the person moves far from a “safe” area, the fitness increases.

- *Sudden Position Changes*

Rapid changes in x and y (and z if available) indicate possible falls.

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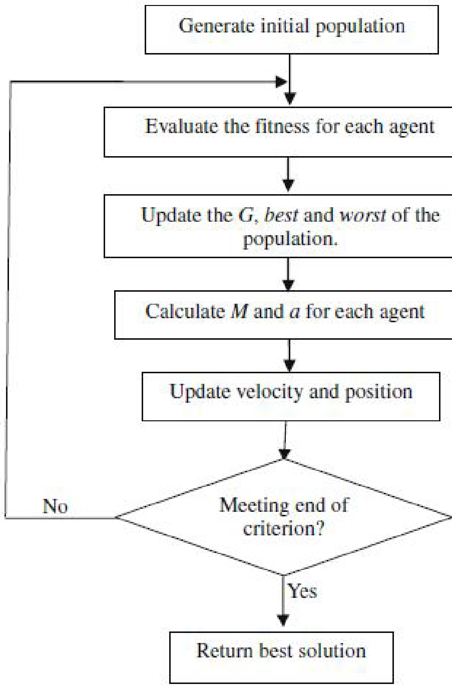

Figure 1: Typical particle swarm optimization flow chart

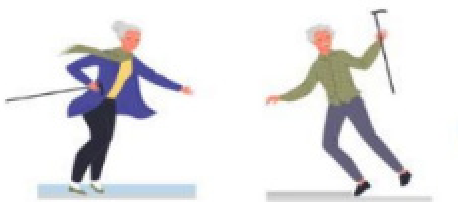

Figure 2: Typical falls in senior citizens

- *Height Change*

A sudden drop in height (z) is a strong indicator of a fall.

Weights

A multiplication factor was used as * 0.1, * 0.5, * 2, etc., defined as weights. These weights were fine-tuned based on various simulations.

Previous Coordinates

To calculate changes in position, we need to keep track of the person's *previous* coordinates. The analysis assumes these are available and are passed to the fitness function. In a PSO implementation, we would typically store the previous position as part of the particle's state.

PSO Integration

In a PSO algorithm, each "particle" represents a possible solution (in this case, this is a set of parameters related to a fall detection model). The particle's position would be the person's coordinates. The function written in Python is what the PSO algorithm uses to evaluate how "good" each particle's position is.

Particle Representation

Each particle in your PSO swarm will represent a set of coordinates (x, y, and optionally z and previous x, y, z).

Fitness Evaluation

The PSO algorithm will use fall detection data randomly generated for each particle, passing the particle's coordinates as the coordinates of the person.

PSO Updates

The PSO algorithm will then use the returned fitness values to update the particles' positions, guiding them towards areas of lower fitness (more likely falls).

RESULTS

Figure 2 depicts a typical fall scenario in citizens. This typically need not be the only case, but can be extrapolated to various types of falls, from a simple fall to a sliding fall or to a similar situation when an elderly person goes down because of low sugar or due to a palpating situation which brings them down. A typical injury biomarker, as shown in Figure 3, might predict

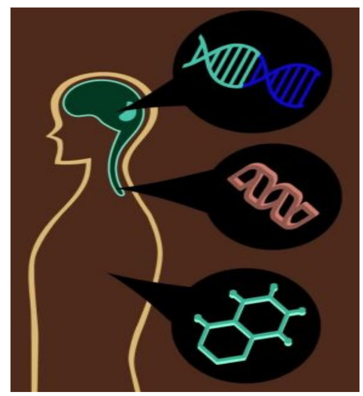

Figure 3: Deep View for injury biomarkers

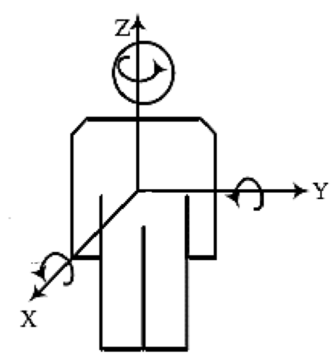

Figure 4: Defining the coordinate system

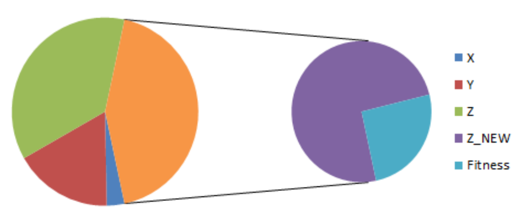

Figure 5: Mapped Pie-Chart analysis for variation

Table 1: Analysis of fall based on random coordinates

X	Y	Z	Z_NEW	Fitness
0.36755	2.02885	4.35672	3.83843	1.31633
1.67468	1.13121	0.28544	1.03108	1.71065
1.41536	1.21176	0.02115	4.6431	9.50679
0.5431	2.58236	3.62065	1.02643	5.57834
0.57822	1.963	2.85236	4.03298	2.63842
0.75447	2.37236	4.77558	1.42214	7.18941
1.42159	0.53117	3.50989	0.82817	5.74915
0.32014	2.23849	1.82878	4.88895	6.41026
0.48654	2.19387	0.54411	3.27938	5.76616
1.90929	1.18148	1.69736	2.44958	1.8863
1.25839	1.11204	1.68289	2.57598	1.9732
0.6689	0.80061	2.74253	1.83713	2.04626
1.29066	1.01334	0.33044	2.72135	5.03576
1.31793	0.20541	3.79623	3.80452	0.29738
1.39094	2.63225	3.75299	0.54938	6.84074
0.70402	0.39465	2.10971	2.94348	1.84355
1.96285	2.03989	1.49554	4.04604	5.4609
1.75979	1.52958	3.48353	1.13963	5.09716
0.93249	1.08386	4.39479	1.30052	6.4535
0.36755	2.02885	4.35672	3.83843	1.31633
1.67468	1.13121	0.28544	1.03108	1.71065
1.41536	1.21176	0.02115	4.6431	9.50679
0.5431	2.58236	3.62065	1.02643	5.57834

the situation of a fall, which can be used as a precursor for the fall as well without actually evaluating the position of the person. The identification of situations that lead to falls using a biomarker is equally challenging.

Figure 4 defines the coordinate system and the variation for the same is studied in Table 1 for variations in the field and the detection of the fall.

Table 1 indicates the data for a typical set of fall variations with x, y and z coordinates changed randomly by the algorithm and the influence of the vertical coordinate Z is mostly important, as in the Z direction, there would be maximum variation during a fall. Hence, the fitness evaluation in column 5 of Table 1 indicates that the fitness variation is higher when the deviation in the Z coordinates of the human stance is higher, as shown in Figure 4.

Figure 5 is the mapped pie chart analysis, which indicates the relative effect of each of the coordinates on the other coordinates and the overall influence on the fitness function. It is clearly seen that the overall function is greatly influenced by the variation of Z, which changes the fitness very much when compared with the other parameters.

CONCLUSION

This study presented a PSO-based approach to enhance fall detection accuracy through sensor fusion and injury biomarkers. The results from simulated data demonstrated the method's potential in elderly care applications. However, the following limitations were identified:

The analysis was based on simulated coordinates, not real-world sensor data, which adds a gap and possible accuracy mismatch in real-world situations.

The dataset consisted of 1000 randomly generated positions, providing a limited evaluation scope, which, given the scope of elderly fall, would vary with the nature of fall due to low sugar levels, stroke, or other possible health reasons and not just a casual slip.

Only the PSO algorithm was explored; However, the authors expect to perform future work with evolving natural-inspired algorithms such as differential evolution, genetic algorithms, which may include comparisons and provide deeper insights into the nature of analysis.

Real-time data integration and clinical validation are proposed for future studies.

Thus, these insights will guide further development toward practical and robust fall detection systems, which will help the elderly receive proper care and attention in time, which is the need of the hour.

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