An Elderly First Aid System Based-Fall Detection and Unmanned Aerial Vehicle

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Abstract. A first-aid system is proposed for monitoring elderly patients who risk falling based on fall detection system (FDs) and for providing the first aid kit from an emergency call centre (ECC) to them by using an unmanned aerial vehicle (UAV). In previous studies, the measurement accuracy of falls and heart rate was not sufficiently accurate. In addition, determination of UAV delivery time is also crucial and can save lives. In this work, the proposed system aims to determine patient falls and accurately measure heart rate and reduce UAV delivery time to patients. The FDs was practically implemented based on heartbeat and accelerometer sensors, a microcontroller, a GSM module, and GPS. While, a UAV, a first aid kit, and Smartphone were adopted in an ECC. Falls were accurately detected based on elderly fall detection (EFD) algorithm. The result showed that the proposed FDs was succeeded in monitoring elderly patients’ vital signs with a fall detection accuracy of 99.11%. In addition, the UAV succeeded in all missions and arrived at the patient’s locations before the ambulance in urban areas, with an average time saving of 1.75 min. The proposed elderly first aid system outperformed previous systems presented in terms of fall detection and UAV arrival time.

Keywords: accelerometer; fall detection; GPS; GSM; heart rate; UAV

1. Introduction
Many elderly people who are childless or have adult children live alone in their house. Often, an elderly person cannot recover from a fall or other critical health event by himself. Thus, they need a smart monitoring device that can automatically detect falling or abnormal measurements of human vital parameters (e.g., temperature (TEMP), SpO2, acceleration, and heart rate (HR)). Some previous researchers have proposed vital parameters monitoring system (VPMS) based on "wireless body-area sensor networks (WBANS)" that can detect falls and monitor the health status of elderly patients by adopting an algorithm, including threshold-based [1], Couple hidden Markov module (CHMM) [2], support vector machine (SVM) [3], and state machine approach [4]. In addition, when critical health status is detected, these devices will obtain the patient’s location and send a notification message to ECC through wireless technology such as GSM [5], ZigBee [6], or Bluetooth [7,8] to inform them that the patient needs first aid [9]. In this work, an elderly first aid system (EFAS) used for detection the falling and monitoring the HR measurements for the elderly patient based on adopted fall detection system (FDs) was proposed. In addition, it can be used for supporting the first aid to the elderly patients after falling by using the unmanned aerial vehicle (UAV) for delivery it to them.

The contributions of the current study can be summarized as follows:

1. An EFAS based on FDs and UAV in outdoor environments was proposed and implemented practically.
2. A new elderly fall detection (EFD) algorithm was proposed to improve the FD for the elderly.
3. Statistical analysis was conducted for FD to confirm measurement accuracy.
4. UAV-based first-aid package succeeded in decreasing the time response relative to an ambulance.
5. Results of this study overcome related studies in terms of measurement accuracy of FD and response time of UAV.

2. Related Works
This section presents previous studies of VPMS regarding measurement accuracy and related works with UAVs are presented.

2.1 VPMS based on measurement accuracy
Zhang et al. [1] enhanced the FD system based on a WBSN technology can use for detection the fall of the elderly. A threshold-based algorithm was adopted by authors for FD. Results indicate that the accuracy for detecting falls is 97.5%, with 98.1% and 96.8% for specificity and sensitivity, respectively. Wang et al. [2] designed a VPMS can measure the patient’s vital parameters. Authors used a CHMM to distinguish human activities. The experiment results have shown, the CHMM classifier can achieve 94.8% of average accuracy. Aguilar et al. [4] established a new technique distinguishing false from an elderly person’s activities daily of living (ADL) based on a Smartphone. A state machine algorithm was adopted as FD algorithm by authors. Experiments show that the accuracy of the proposed FD algorithm is 97.5% for pocket and belt locations. Gharghan et al. [10] proposed indoor FD systems for the elderly based on Zigbee technology. The authors proposed an algorithm for sensor-based FD. In addition, they adopted an artificial neural networks (ANN) algorithm for determining the elderly person location. The results showed that the elderly wearing the system when falling can be detected in “non-line-of-sight” environments with an accuracy of 92.5% and a 0.0454 m of a mean absolute error for indoor localization error.

Rihana et al. [11] designed and implemented an FD and alert system for elderly persons based on GPS and GSM/GPRS. The authors adopted an FD algorithm based on an acceleration threshold. The results indicated that the developed prototype showed satisfactory performance, with a sensitivity of 90%, the specificity of 85% and an accuracy of 87%. Authors in [12], was improved a VPMS based on a WBSN that can track the signals of human physiological. They investigated the measurements by using an examination scenario during common ADL. Results indicate that the proposed system can detect all activities with an accuracy of 95%. Cheng et al. [13] established a new technique of process for ADL and FD monitoring based on adopted two sensor signals such as an accelerometer (ACC) and “surface electromyography (SEMG)”. A histogram negative entropy and “double stream hidden Markov module (HMM)” algorithms were adopted to determine static and dynamic active segments. Results show the new technique can classify between ADL and FD with an accuracy of greater than 98%.

Related work [14] was introduced a novel way to measure the distances to recognize person activities based on sensors motion. They proposed a “Log-Sum Distance” algorithm to measurements the distance. The results show, the proposed algorithm can detect the activities with an accuracy of 99%, and it can decrease the incorrect classification rates by using threshold values to classify activities. Wu et al. [15] established a novel device for FD based on a WBSN which can be used for the elderly when falling. Acceleration threshold and rotation angle algorithm were adopted by authors for detecting the fall. Results revealed that the new system could achieve 97.1% for sensitivity. Mezghani et al. [16] improved a device used for FD based on a machine learning technique and smart textiles. The authors used a non-linear SVM to detect the orientation of falling. The results indicate that the proposed system has 98% and 98.5% accuracy of FD and fall orientation, respectively. Other related works such as [17] have enhanced FD systems for the elderly based on WBSNs. The authors adopted hardware components to design and implement the proposed systems such as an ACC sensor, GSM module, GPS module, and microcontroller. The results show that the proposed systems enhanced the accuracy of FD and were reliable when used by elderly patients outside the hospitals. The comparison of the studies mentioned and discussed above is summarised in table 1.
Table1. Comparison of previous works related to VPMS.

| Reference /Year | Adopted wireless technology | FD algorithm | Types of sensor | Location of sensor nodes | FD accuracy (%) |
|-----------------|----------------------------|--------------|-----------------|--------------------------|-----------------|
| [6]/2010        | ZigBee                     | Threshold-based | ACC             | Waist                    | 96.92 (FD)      |
| [7]/2010        | Bluetooth                  | Threshold-based | ACC             | Chest                    | 95.67 (FD)      |
| [13]/2013       | Bluetooth                  | Entropy, HMM  | -SEM              | Leg                      | >95 (Entropy and HMM) |
| [1]/2014        | Zigbee                     | Threshold-based | -ACC             | N/A                      | 97.5 (classification) |
| [2]/2014        | Zigbee                     | CHMM          | -ACC             | -Wrist                   | 94.8 (CHMM)     |
| [4]/2014        | Smartphone                 | State machine | ACC             | Pocket Belt              | 97.5 (Pocket and Belt) |
| [12]/2014       | Bluetooth                  | Threshold-based | -ACC             | Chest                    | 97 (ACC)        |
| [5]/2016        | GSM                        | LA-TPDC       | -ACC             | Upper arm                | 90.2 (posture and activity) |
| [11]/2016       | GSM                        | Threshold-based | ACC             | Waist                    | 87 (FD)         |
| [17]/2016       | GSM                        | Threshold-based | -ACC             | N/A                      | 97.5 (FD)       |
| [3]/2017        | Bluetooth                  | SVM, KNN      | -ACC             | Waist                    | 97 (classification) |
| [8]/2017        | Bluetooth                  | SVM, KNN      | ACC             | Wrist                    | 98 (SVM)        |
| [14]/2017       | Bluetooth                  | Log- Sum      | ACC             | Ankle                    | 96.13 (KNN)     |
| [16]/2017       | Bluetooth                  | Non-linear + | Smart textiles   | Belt                     | 98 (FD)         |
| [10]/2018       | Zigbee                     | ANN           | -ACC             | Waist                    | 92.5 (FD-NLOS environment) |

ACC: Accelerometer; HMM: Hidden Markov module; SEMG: Surface electromyography; CHMM: Couple hidden Markov module; TEMP: Temperature; HUM: Humidity; FD: Fall detection; KNN: K-Nearest neighbor; HB: Heartbeat; ANN: Artificial neural network; LA-TPDC: Linear Acceleration based on Transmission Power Decision Control; SVM: Support vector machine;

2.2 UAV based on response time

Previous works such as [9,18–21] which adopted the UAV as a transportation method for delivering the medical products [21], first aid kit [20], a medical device such as automated external defibrillator (AED) [9], and fire extinguishing ball. These related studies were interested in decrease the time response by adopted some of path planning algorithms such as a multi-criteria evaluation (MCE) [9], maximum coverage location problem (MCLP) [19], etc. In addition, the required time by UAV to reach the patients were determined and compared by authors according to the adopted algorithm with arrival time of emergency medical service (EMS) such as an ambulance. Claesson et al. [9] development a project for transported the AED to the patients who have a cardiac arrest in out of hospital-based on UAV. A “geographic information system” (GIS) was used by authors to determine travelling times. Results shown, the UAV arrived before EMS in the urban area to the patients in 32% of cases with time savings (1.5-minute). Whereas, the UAV arrived at the patient's (in the rural areas) in 93% of cases and time savings (19 minutes). Kumar et al. [20] proposed a first aid delivery system to sportsmen who injured in outdoor during ADL by using a UAV as an ambulance. A smartwatch was adopted in this project for tracking the location. Results show that the new system is low-cost, decrease the response time, and
provides good medicinal service, and low power consumption. Table 2 presented the comparison of the previous studies which discussed in above as below:

**Table 2.** Comparison among UAV-related works.

| No. ref/year | Path planning Algorithm | Response time (min) | First aid equipped |
|--------------|-------------------------|---------------------|--------------------|
| [21]/2015    | N/A                     | Less delivery time  | Medical products packages |
| [9]/2016     | MCE                     | -1.5 (Urban)        | AED                |
|              |                         | -19 (Rural)         |                    |
| [19]/2016    | MCLP                    | 1                   | AED                |
| [20]/2017    | Python                  | N/A                 | - First aid kit.   |
|              |                         |                     | -fire-extinguishing ball. |
|              |                         |                     | -HR monitor.       |
| [18]/2017    | Python                  | N/A                 | AED                |
|              |                         |                     |                    |

MCE: multi-criteria evaluation; AED: Automated external defibrillator; MCLP: maximum coverage location problem.

3. Methodology

This section presented the EFAS system structure, proposed FDs hardware, EFAS evaluation, and system algorithm.

3.1 Elderly first aid system structure

An EFAS consists of two main parts as shown in Figure 1. The first part was represented as an FDs which can be used for monitoring the elderly patient. It has consisted of a microcontroller, heartbeat (HB) sensor for HR measurements, ACC sensor for acceleration measurements [22], a GPS board for tracking the elderly location, and GSM module that adopted to send the messages from FDS to the caregivers in the ECC. The second part as shown in Figure 1 is the ECC’s which used for provided the first-aid package to the elderly when critical cases. ECC contains Smartphone, first-aid package, and the UAV for transportation [23]. The main principle of an EFAS includes attached the FDs to the upper arm of the patient for monitoring and decision-making when falling occur. If fall occurs, the FDs will send messages to Smartphone which located with caregivers in ECC. In this current study, Smartphone was adopted for two missions. The first mission, to receive SMS from the FDs. Whereas, the second mission was used to planning the path of flight for the UAV [24]. After receiving SMS and drawing flight path by Smartphone, the kit (first aid) will be attached to the base of the UAV by caregivers and send to the patient location.

![UAV sent according to path planning](image)

**Figure 1.** Block diagram of the overall EFAS.
3.2 Proposed FDs hardware

Figure 2 shows the hardware of proposed FDs which consisted of five hardware components such as a microcontroller-based Arduino Pro Mine, HB sensor based on pulse sensor, ACC sensor-based ADXL345, NEO-M8N was adopted a GPS, GSM modules based on SIM800L, and battery lithium-ion (3.7v/4200 mAh). The ADXL345 can be powered by DC voltage from the 3.3 V pin of the microcontroller. The data recorded by the ACC sensor are transferred to the microcontroller via the SDA and SDL pins through a serial digital interface (SPI). In addition, the ACC sensor was calibrated by invited five elderly volunteers aged (60 to 64 year) and four types of normal activities (i.e., running, sitting, walking, and standing) and four types of fall were adopted to distinguish between each type of activities for each volunteer and to selected the suitable fall detection threshold for FDs. In this work, the adopted microcontroller was used to do three missions. The first mission, it is used for receiving the acceleration measurements signals from ACC sensor. The second mission includes processes the received data to extract the x-axis, y-axis, and z-axis accelerations. The values of these axes can be utilised to calculate the acceleration magnitude $|A|$ based on Equation (1) [25], as defined below.

$$|A| = \sqrt{A_x^2 + A_y^2 + A_z^2}$$

where $A_x$, $A_y$, and $A_z$ represent the acceleration of the three axes $x$, $y$, and $z$. The third mission of the microcontroller is decision making by comparing the measurements of $|A|$ with adopted fall detection threshold. If the microcontroller detects the value of $|A|$ less than the fall detection threshold. When the microcontroller decides the patient is falling, it was going to check the HR measurements signal through the serial port (A0), getting the geolocations of him/ her based on GPS via serial port (Rx), and sent the information’s of the patient through GSM module to ECC.

![Figure 2: The hardware of the overall FDs.](image)

3.3 EFAS evaluation

The evaluation performance of whole EFAS can be divided as follows:

3.3.1. Fall detection system validation

Evaluation of the EFD algorithm performance was done by inviting three volunteers and attach the FDs to the upper arm. The upper arm was adopted as the sensor node because it has high skin conductivity and more sensitive to the HR and less movement for ACC sensor to distinguish between falls than ADL. Each volunteer achieved a scenario that involves three phases of activity (i.e. standing, running, and falling dependent on the time required for each phase), as shown in table 3. A treadmill was adopted in the FDs experiment to estimate the three phases.
Table 3. Scenario to evaluate the performance of the EFD algorithm.

| No. of Phase | Phase 1 (standing) | Phase 2 (running) | Phase 3 (falling) |
|--------------|--------------------|-------------------|-------------------|
| Time of each Phase (min) | 1 | 3 | 1 |

The total data collected from all phases included 300 samples for each volunteer. The collecting data were inspected and validated based on statistical analysis to determine the accuracy of FD based on Equation (2), as below [25]:

\[
\text{Accuracy} = \left( \frac{TN + TP}{TN + TP + FN + FP} \right) \times 100 \%
\]  

where TP is representing the number of falls (true classified), TN which represent the number of ADL (true classified). Whereas FP and FN are representing the number of ADL (false classified), and the number of falls (false classified), respectively.

3.3.2 Heartbeat sensor validation relative to the benchmark

The HR measurement of adopted HB sensor was validated relative to consumed ready device as a benchmark (BM) system based on the patient monitor (Üzümçü VISIO ECO) [26], as shown in Figure 3. The adopted BM system was already calibrated and has a high accuracy of HR measurement. The experiments of HR done by invited three volunteers and attached both HB sensor of the FDs and BM devices to each volunteer at the same time. Total data recorded from three volunteers were 180 samples of HR measurements from each device (FDs and BM). All data records were examined and validated based on statistical analysis such as mean absolute error (MAE) based on Equation (3) [10] as defined below:

\[
MAE = \frac{1}{m} \sum_{i=1}^{m} | x_i - y_i |
\]  

where \( m \) is the number of measurement samples. The \( x \) was the HR measured by the FDs and \( y \) is the HR measured by the BM device.

3.3.3 UAV response time experiment and validation

PAR hospital in Iraq was represented as the ECC. It will be used to sends the UAV and ambulance to the adopted patient location, as shown in Figure 4. Four locations were precisely selected which it was crowded and hard to access.
Figure 4. UAV and ambulance send to the patient from ECC.

Time-saving was very important and represented as the reduction for the required time to deliver the first-aid package to the location of the patient. It can calculate based on Equation (4), as below:

\[
Time\ savings = Timespent_{ambulance} - Timespent_{UAV}
\]  

(4)

Average time savings for the adopted sites can be calculated based on Equation (5), as defined below:

\[
Average\ timesavings = \frac{1}{k} \sum_{i=1}^{k} Timesavings_i
\]  

(5)

where k represents the number of adopted locations.

3.4 System algorithms

The EFAS based on an FDs for elderly health monitoring and UAV that used to provide first aid to them. To successfully these missions, the EFAS required to designed a two new algorithm for the FDs and ECC, separately. It was clarified as below:

- When body fall and detection by proposed EFD algorithm, the FDs will be going to check the HR measurements of the patient and send SMS messages to caregivers in the ECC which contains the information of the patient (i.e., patient falls, and geolocation information), as shown in Figure 5a.

- Regarding ECC, the messages send from FDs was receives on the Smartphone. After that, the package of first-aid will be equipped based on the information received from FDs about the patients after fall and sent to the location through the UAV according to path planning, as shown in Figure 5b.

![Figure 5. Overall EFAS algorithm for (a) EFD, and (b) ECC.](image-url)
4. Results and Discussions
Result of the FDs in term of FD and the result of the UAV in term of time response will presents separately as below:

4.1 Fall detection
Figure 6 illustrations the validation results for the EFD algorithm experiment. Samples were gathered every second, and the total examination time was 900 s for three volunteers (900 samples collected for all volunteers). Figure 6a illustrate the result of acceleration measurements for the first volunteer, it was reached 0.16 g when falling. The second volunteer reached 0.39 g of acceleration when fall, as shown in Figure 6b. Finally, the result of acceleration measurements for the third volunteer as shown in Figure 6c, it recorded when falling 0.34 g. Generally, the overall results for all volunteers show that the EFD algorithm for the FDs was successful in the FD.

![Acceleration magnitude vs. Time](attachment:image1.png)

**Figure 6.** EFD algorithm evaluation for each volunteer: (a) 29, (b) 33, and (c) 34 years.

4.2 HR measurements
The MAE was employed in this works to determine the difference between the HR measurements of proposed FDs and BM device. As shown in Figure 7, the error fluctuates between the range of 0 and 7, with the highest error value of 7 bpm. The results of the HB sensor experiments appeared the adopted pulse sensor of the proposed FDs was more accurate, and it has 2.72 of the MAE.
4.3 UAV time response

Four patient locations were adopted to send the ambulance and UAV according to the flight paths. The arrival times, time savings, and average time savings for the UAV and ambulance were calculated for each location and presented in Table 4. In locations 1 and 2, the UAV consumes 3.5 min to reach the two locations (1.5 min before reached the ambulance). Whereas, UAV arrived locations 3 and 4 in 4 min compared to 6 min of the ambulances for a time saving of 2 min. The results revealed in urban areas that the UAV arrived at all patient locations before the ambulance with an average time savings of 1.75 min.

| Patient Location | UAV arrival time (min) | Ambulance arrival time (min) | Time savings (min) |
|------------------|------------------------|-----------------------------|--------------------|
| Locations 1 & 2  | 3.5                    | 5                           | 1.5                |
| Locations 3 & 4  | 4                      | 6                           | 2                  |
| Average time    | 3.75                   | 5.5                         | 1.75               |

4.4 Comparison results with related works

Accuracy of FD for proposed EFD algorithm was depended on the acceleration magnitude threshold. Related work has presented FD systems that use FD algorithms such as KNN [3], threshold-based [12], and state machine [4]. In this work, the proposed EFD algorithm has achieved 99.11% accuracy of FD with 99.12% of sensitivity. The results for the EFD algorithm could be compared with other related studies as shown in Figure 8. The implemented EFD algorithm is superior to other related systems in FD accuracy.

Figure 7. MAE measurements of the FDs relative to BM device.

Figure 8. Comparison of the FD accuracy for the FD system with related works.

Regarding UAV response time, related works who adopted UAV for first-aid transportation were focused on decrease the time arrival by proposed and adopted a new flight path algorithm to path
planning of UAV. In this work, the adopted Autopilot algorithm based on Smartphone which used for path planning was succeeding in decrease the arrival time of the UAV with 1.75 min (average time savings) compared with an ambulance. Figure 9 shown the compared between the response time by UAV of the EFAS with other same related works who adopted UAV.

![Comparison between the UAV time response with other works.](image)

**Figure 9.** Comparison between the UAV time response with other works.

5. Conclusion and Future Work
This study presented new elderly first aid system van be used for monitoring the FD of elderly patients based on a proposed FDs and to deliver the first aid kit to them when falling by using the UAV. The proposed FDs was designed as a small size and suitable to wearable in the upper arm of the body. The FDs consists of a microcontroller, GPS module, GSM module, ACC sensor, and HB sensor. A new FD algorithm for predicting falls was presented for the FDs, named the EFD algorithm. The EFAS displayed high FD accuracy results (99.11%) with 2.72 of MAE for HR measurements of FDs. In addition, the average time savings of proposed EFAS was 1.75 min when using the UAV than an ambulance when transporting the first aid. Therefore, the proposed EFAS has exhibited excellent results in term of FD accuracy and response times when sending the first-aid kit through UAV. This EFAS will be suitable for future studies in the field of VPMS and provider of first aid. The limitations of the current study include (i) motion artifacts during physical activities represented an obstacle when measuring the HR because the HB sensor was more sensitive to the motion artefact, which can decrease the accuracy of the measurement, (ii) some of the fall types such as falling from the bed cannot detected by the ACC sensor and did not reach the adopted fall threshold, and (iii) regarding to the experiments of time-savings based on the UAV, the analysis would have benefited from considering more locations to measure the arrival time of the UAV, but this was not carried out due to security concerns that prevent UAV flight. Future study will interest in increase and improve the FD accuracy. Future work will focus in design an autonomous system using the acquired longitude and latitude of the patient from the GPS and send a “first aid kit” through a UAV to the location of patient without human intervention.

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