Internet of Things for Fall Prediction and Prevention

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Abstract—Internet of Things (IoT) is making a breakthrough for the development of innovative health-care systems. IoT-based health applications are expected to change the paradigm traditionally followed by physicians for diagnosis, by moving health monitoring from the clinical environment to the domestic space. Fall avoidance is a field where the continuous monitoring allowed by the IoT-based framework offers tremendous benefits to the user. In fact, falls are highly damaging due to both physical and psychological injuries. Currently, the most promising approaches to reduce fall injuries are fall prediction, which strives to predict a fall before its occurrence, and fall prevention, which assesses balance and muscle strength through some clinical functional tests. In this context, the IoT-based framework provides real-time emergency notification as soon as fall is predicted, mid-term analysis on the monitored activities, and data logging for long-term analysis by clinical experts. This approach gives more information to experts for estimating the risk of a future fall and for suggesting proper exercises.

Keywords—Health care, fall avoidance, gait analysis, accelerometer, gyroscope.

I. Introduction

Internet of Things (IoT) has gained rapid attention from expansion of the Internet. In the wider vision of the IoT, *anything* would be connected to the Internet [1]. IoT connects sensors, actuators, devices, etc. to the Internet and is conceived as an enabling technology to realize the vision of a global infrastructure of networked physical objects. Among the innumerable application fields of IoT, such as traffic management [2], agriculture [3], and smart home [4], health care is one of the most attractive for researchers. In fact, recently much research in the areas of Engineering and Mathematics focused on health care [5], [6]: IoT has the potential to improve existing medical applications by enabling remote health monitoring, with treatment and medication at home supplied by health-care providers. Remote health monitoring systems promise to revolutionize the conventional health-care methods by integrating the IoT paradigm [7]. With respect to clinical measurements, IoT-based solutions can readily gather data with finer temporal sampling over longer longitudinal time scales. Long-term data observation makes data analysis more efficient: machine-learning algorithms can recognize correlations between sensor observations and clinical diagnoses.

Health-care applications for fall avoidance can gather promising benefits from IoT. Physical injury is not the only negative consequence of a fall, as there is often a psychological impact on the quality of life. Therefore, it is critical to provide integrated health-care facilities that fully addresses both physical functioning and psychological well-being.

Fall avoidance systems can be categorized into three groups: detection, prediction, and prevention systems. Fall detection systems notify an acquaintance of a user in case of fall occurrence [8, 9]. These systems provide fast help after a fall, without avoiding it, so they are less effective than the other systems. Fall prediction systems identify an abnormal walking pattern, and estimate the probability of a real-time fall occurrence [10, 11]. Fall prevention systems exploit some clinical tests to assess the risk of future falls and to suggest proper solutions for preventing them [12, 13]. These tests often involve functional assessments of posture, gait, cognition, and other fall risk factors. The computational capabilities of IoT nodes offer new perspectives for the combination of real-time fall prediction and prevention of future falls, as described in Section II. Three levels of analysis are available: real-time, mid-term, and long-term analyses are presented in Section III, IV, and V respectively. Finally, some conclusions are drawn in Section VI.

II. IoT-based framework for fall avoidance

Adding IoT features to a fall avoidance system leads to interesting benefits. First, it significantly extends the scope and coverage of the traditional health-care information system, moving it from a clinical environment to the user's home. Secondly, the computational capability becomes virtually unlimited, so allowing the execution of a full range of fall algorithms, including both real-time fall prediction and future fall prevention.

Fig. 1 illustrates the conceptual view of the novel model. The main components of the system are:

- User monitoring: sensors monitor the kinematic characteristics of the user. The sensors are embedded in a smartphone or integrated into the domestic environment.
- Real-time analysis: the smartphone can perform basic computation tasks for real-time fall prediction.
- Mid-term analysis: the smartphone and the domestic sensors connect to an intermediate data aggregator through a WiFi network, which is typically a local gateway in the vicinity of the user. Then, the gateway can implement more detailed procedures for real-time fall prediction.
- Cloud storage: the gateway conveys the aggregated data to the cloud storage.
- Long-term analysis: experts in a health-care institute analyze the acquired data.

The user’s smartphone and the domestic sensors are the *basic IoT nodes*. The smartphone offers compliant computational power, essential sensors, and communication capability. Fall prediction systems monitor users with common sensors, such as accelerometer and gyroscope, which are available in almost all smartphones. Furthermore, features extracted from accelerometer and gyroscope embedded in a smartphone are verified to be precise enough for fall algorithm [14]. The smartphone executes a light machine-learning algorithm to analyze the collected data in real-time in order to predict a fall. Domestic sensors can collect additional data for further analysis. In particular, sensors of floor vibrations and sounds are the most promising for fall prediction [15].

The smartphone and the domestic sensors send the collected data to a local node, called *IoT gateway*. The IoT gateway is a processing device close to the user in order to augment the computational capability of the smartphone. Furthermore, it aggregates data collected from different sources. In this way, impractical management of numerous data is avoided, deeper investigations can be performed by considering complementary features, and data are presented to expert in an intuitive format for readily comprehending inter-relationships. Finally, the IoT gateway stores the data in a cloud storage for long-term data analysis. This analysis is essential to prognosticate user's malady.

The IoT-based framework is intended for home scenarios, so health-care operators in hospital can monitor the condition of subjects residing at home. In fact, the layered architecture shown in Fig. 1 allows three different types of data analysis. Real-time analysis can be performed with the smartphone, mid-term analysis is executed by IoT gateway, and long-term analysis is postponed to the hospital.

III. Real-time data analysis

In the first layer of the IoT-based framework, an imminent fall is predicted by means of the sensors embedded in the smartphone. Basically, the smartphone monitors the user activity and it exploits a lightweight algorithm to predict the fall, due to the limited computational capability. An imminent fall can be easily deduced by comparing the measurements with the expected data, as computed with a prediction model. Generally, the prediction model is a discrete-time nonlinear system that considers the last n instants:

$$\hat{y}_{t+k} = f(y_t, y_{t+1}, \dots, y_{t-n+1}) = f(q_t)$$

where y_t is the output of the sensors at time t, q_t is the set of the last n sensor measurements, $\hat{y}_t$ is the predicted output by assuming a normal walk and k is the prediction horizon. The function implemented in the prediction model can be expressed as a sum of N terms:

$$f(q_t) = \sum_{i=1}^{N} a_i \;\; \Phi_i(q_t) = a\, \Phi(q_t)$$

where $\Phi(q_t) = [\Phi_1(q_t), \Phi_2(q_t), \dots, \Phi_N(q_t)]$ are known basis (e.g., polynomial) functions and $a = (a_1, a_2, \dots, a_N)$ is a coefficient vector. In order to determine the best coefficient vector a^0, a set $\tilde{y} = (\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_L)$ is preliminarily collected, then the following optimization problem is solved [16]:

$$a^0 = \arg\min_{a \in R^N} \|a\|_0 \quad \text{subject to } \|\tilde{y} - \Phi(\tilde{q})a\|_2 \leq \varepsilon \,.$$

Since this approach is exploited in real-time, a simple prediction model is preferred, by considering only acceleration signals [17]:

$$y_t = \sqrt{A_x^2(t) + A_y^2(t) + A_z^2(t)}$$

where $A_x^2(t)$, $A_y^2(t)$, and $A_z^2(t)$ are the acceleration components along the three axes. The settings for the other parameters are k = 1 and N = 8: they are obtained by validating the model with another set of data, consisting of both normal and abnormal walking patterns. The output predicted by the model during normal walk is satisfactorily close to the data collected in the validation set. Instead, there is a large difference between predicted and real data in case of an abnormal user behavior. Therefore, a threshold-based algorithm is used to classify the user gait. An abnormal walk, with an increased risk of fall, is detected if the following condition does not hold:

$$1 - \frac{\|y - \hat{y}\|_2}{\|y - \text{mean}(y)\|_2} < \delta$$

where the value of threshold δ is empirically set. This approach needs little time to detect an abnormal behavior, due to the low overhead in managing the values collected by the smartphone sensors.

IV. Mid-term data analysis

In the second layer of the framework, a near gateway receives the collected data for supplementary analysis and data aggregation. The data collected by the smartphone can be analyzed more in detail. In fact, the real-time analysis performed by the smartphone was focused on the raw data, due to the limited computational capability. Instead, the IoT gateway can extract features from the raw data and then it implements a more complex algorithm for fall prediction. At the same time, the IoT gateway can apply different fall-prediction techniques based on the data received from the domestic sensors.

The raw data received from the smartphone can be efficiently arranged into a co-occurrence matrix. This square matrix shows the scattering of similar adjacent values at a given offset. Co-occurrence matrices are commonly adopted for image processing [18], but their application in fall prediction has been investigated recently [19]. Fig. 2 shows an example of the co-occurrence matrix obtained from accelerometer and gyroscope signals. First, the acceleration and gyroscope data are stored in a matrix Δ: each column of the matrix presents a sample per instant. The number of columns depends on the length of the monitoring interval, as one column is added at every instant. This matrix has 6 rows: at every instant, 3 values are obtained from the accelerometer and 3 from the gyroscope. Then, each cell of the co-occurrence matrix is initialized to zero. Then, each couple of consecutive cells in Δ is analyzed to find similar patterns. Finally, the number of similar patterns is reported in the co-occurrence matrix at the coordinates given by the cell content.

Useful features can be extracted from the co-occurrence matrix. Let p_{ij} be the ratio of the (i, j)th element of the co-occurrence matrix to the sum of all the elements. The main indices that characterize a co-occurrence matrix are [18]:

- *contrast* measures the differences between a cell and its neighbors:

$$\text{contrast} = \sum_i \sum_j (i-j)^2 p_{ij}$$

- *homogeneity* shows the spatial closeness of the elements to the diagonal of the matrix:

$$\text{homogeneity} = \sum_i \sum_j \frac{p_{ij}}{1 + |i-j|}$$

- *correlation* indicates the dependence between a cell and its neighbors:

$$\text{correlation} = \sum_i \sum_j \frac{(i - m_r)(j - m_c)p_{ij}}{\sigma_r \sigma_c}$$

  where $m_r = \sum_i \sum_j i p_{ij}$, $m_c = \sum_j \sum_i j p_{ij}$, $\sigma_r = \sum_i \sum_j (i - m_r)^2 p_{ij}$, and $\sigma_c = \sum_j \sum_i (j - m_r)^2 p_{ij}$.

- *uniformity* is the sum of the squares of the values.

- *maximum probability* is the highest value of the co-occurrence matrix.

In order to exploit the features extracted from the co-occurrence matrix for the fall prediction, a new matrix Γ is built by placing side by side the contrast, homogeneity, correlation, uniformity, and maximum probability of all samples. For every row in Γ, the average value of the row is subtracted from all its elements, in order to build a new matrix Θ. Finally, the eigenvectors of $\Theta\ \Theta^T$ are computed. As these eigenvectors describe walking features, they are called *eigenwalks* [19]. The eigenwalks can discriminate between normal and abnormal walking patterns. The relaxation of computational constraints, due to the higher performance of the IoT gateway with respect to the smartphone, allows the implementation of classification algorithms other than the threshold-based one, such as decision tree, support vector machine, multilayer perceptron and random forest.

Different fall prediction techniques can be implemented by analyzing the data collected from the domestic sensors. Useful information can be obtained from sensors of floor vibrations and sounds. In fact, abnormal gait creates a shock signal that propagates in the floor. Among the lot of sounds in the house during the daily routine, special combination of vibration event with proper sound event can be indicative of an increased risk of future fall. Sound sensor are commonly used in gait analysis and fall detection systems [20, 21, 22, 23] but here the novelty is to exploit them to predict a fall. A combination of vibration and sound sensors, with accelerometer and microphone sensors, can reveal useful information about abnormal gait. The microphone is the most critical sensor in this context. Microphones are commonly classified in types ranging from 0 to 2, according to their tolerance and accuracy [24]. Type 0 refers to laboratory microphones: they are extremely accurate but they may not satisfy environmental requirements. Microphones of type 1 are exploited both in laboratory and field, as they are extremely accurate and durable. They are designed to provide highly accurate and reliable acoustic measurements, despite environmental noise. Microphones of type 2 are general purpose: they do not have high-frequency response, low cartridge thermal noise levels, or accuracy as the first two types, but they offer a less expensive alternative when the measurement accuracy is not critical. Table 1 shows a comparison of the different types of microphones. Since the quality of the sound is important in the context of fall prediction, the most appropriate microphones are Electret and MEMS (Micro Electro-Mechanical System). Electret microphones are small and effective at detecting high-frequency sound. They are relatively cheap, and their only drawback is the lack of bass provided. The MEMS microphones include a pressure-sensitive diaphragm, which is etched directly into a silicon wafer, and is usually accompanied with integrated preamplifier. Digital MEMS microphones have built in analog-to-digital converter (ADC) circuits on the same CMOS chip making the chip a digital microphone and so more readily integrated with modern digital products. However, MEMS microphones have lower vibration sensitivity than electret microphones.

V. Long-term data analysis

In the third layer of the IoT-based framework, the data aggregated by the IoT gateway are sent towards the cloud storage for further analysis. In this way, experts can assess the future fall risk of the user through a continuous physiological monitoring.

Typically, prediction of a future fall is based on offline tests for evaluating balance and lower limb strength, such as timed up and go (TUG) [25], Berg Balance Scale (BBS) [26], sit to stand (STS) [27], and one leg stand (OLS) [28]. If the fall risk is high, a probable future fall can be prevented through some exercises [13].

In the TUG test, a user is asked to rise from an arm chair and walk at a line on the floor three meters away, turn and walk back to the chair and sit down again. A performance higher than a threshold leads to a high risk of falls.

The BBS test measures the user's balance by assessing the performance in carrying out a set of tasks. A score expresses the degree of success in each task, and the fall risk is deduces from the sum of all the scores.

In the STS, firstly, the user sits in the middle of a chair, with each hand on the opposite shoulder. He rises to a full standing position and then he sits back down again. Eventually, this test counts the number of full stands that is completed in 30 seconds. Since slowing of postural movements can be an indicator of the weak lower limb, a low number of full stands shows a high risk of a fall.

The OLS test evaluates the user's balance. The user raises one leg after the other with the foot approximately six inches off the ground, keeping the foot raised up for 30 seconds. The user is allowed to sway side-to-side or back-and-forth while maintaining the one-leg stand position, but if he puts his foot down some times during the 30-second period, then he fails the test.

Typically, the mentioned tests are executed in clinical environments. With the IoT-based framework, the user is free to choose when and where execute the tests. The tests can be repeated more frequently, therefore increasing the amount of available information. The results are recorded and then remotely analyzed by experts. According to results, the experts can suggest proper exercises to reduce the risk of future falls.

VI. Conclusion

Internet of things enables innovative fall risk avoidance systems. The presented framework steps forward in gait analysis by providing an effective means of capturing and processing data, both on-line and off-line. In particular, three different types of data analysis are available: real-time and mid-term data analyses are intended for fall prediction, whereas long-term analysis is suitable for fall prevention. Data are collected by sensors embedded in a smartphone or integrated into the domestic environment. Afterwards, data are aggregated and stored in the cloud, so clinical experts can remotely access them.

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Microphones	Price	Environment	Impedance Level	Sensitivity	Advantages
Prepolarized Condenser	Medium	Tough	Medium	Best	Best in humid environments
MEMS (Micro Electro-Mechanical System)	High	Tough	Medium	Best	Best in high-temperature environments
Carbon Microphone	Low	Average	High	Good	Used in basic design of telephone handset
Electret	Low	Average	Low	Very good	Suitable for high frequency
Piezoelectric	Medium	Tough	High	Good	Suitable for shock and blast pressure measurement applications
Dynamic/Magnetic	High	Tough	Medium	Very good	Resistant to moisture

Table 1: Comparison among available microphones.

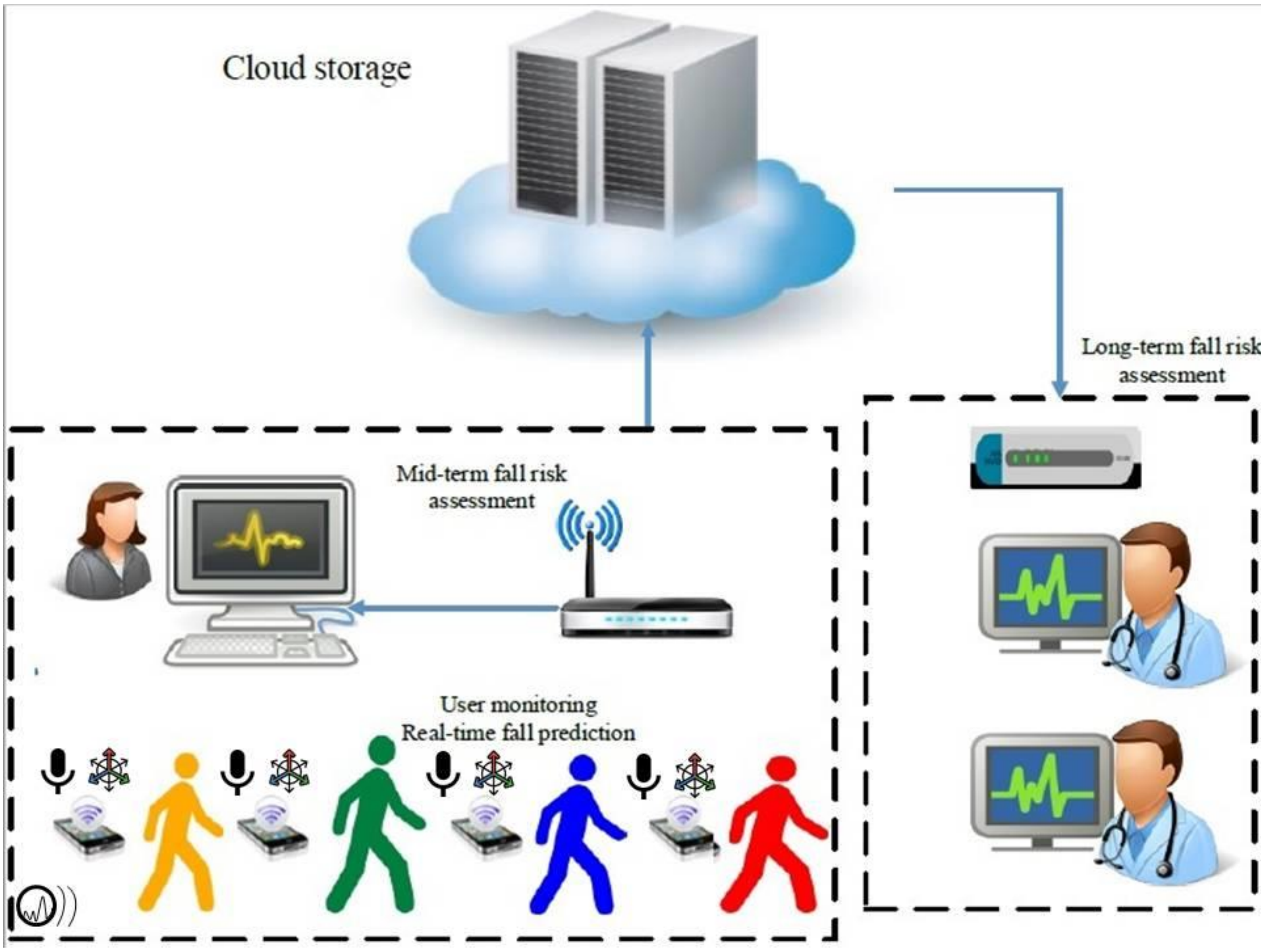

Figure 1: Conceptual view of the IoT-based framework

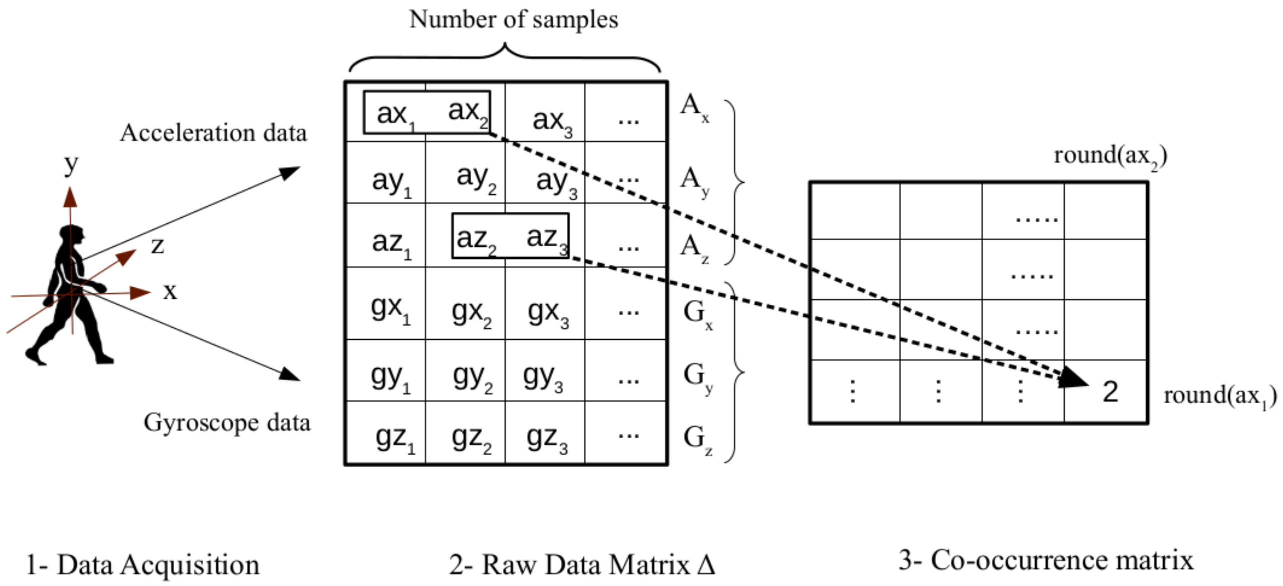

Figure 2: Computation of the co-occurrence matrix.