AN INTEGRATED SYSTEM FOR INDOOR PEOPLE LOCALIZATION, TRACKING, AND MONITORING

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Abstract

Human activity monitoring technologies are one of the essential systems for elderly care. Advances in electronic systems, sensor technologies, and communication network protocols have enabled a new generation of integrated health systems to be created. The solution presented in this document represents an integrated system prototype that provides an efficient technological tool to caregivers operating promptly and ensures efficient performance throughout the entire healthcare system process. This solution differs from previous works for the coexistence of a series of innovative aspects. Human activity recognition is based on combining different types of information: environmental data, physiological data, inertial data, and indoor location data of patients; CNN network for locating position and activities; Virtual Reality System (VR) for optimizing the neural network and related training.

Keywords: *Inertial sensors, environment sensors, indoor positioning, human activity, convolutional neural networks, virtual reality*

1. SOCIAL CONTEST

Rapid population growth associated with the increase of independent people requires societies worldwide to radically change their approach to the care system for older people. Unfortunately, the lengthening of life does not go hand in hand with maintaining good health conditions or conditions that are sufficiently compatible with autonomous life management. Today, an ever-increasing number of older people live alone (over 32%) for many factors, first of all, the death of their spouse. Needs have emerged linked to the enlargement of the range of users and the topology of problems presented by people. The incidence of particularly disabling diseases such as senile dementia and, in particular, Alzheimer's disease increases with advancing age and constitutes a growing medical, social, welfare, and economic challenge since the highest percentage of ill subjects is found in more advanced age groups. Dementia interferes with people's autonomy and dignity and causes suffering for patients and family members.

The rapid growth of this type of population is imposing an increase in the demand for health and social health services in hospitals, nursing homes, and homes. Older people who cannot take care of themselves must give them special assistance during daily care.

Until now, the family has guaranteed long-term care, but society, family, and the labor market are changing profoundly: the women who represented the main focus in the role of family care are increasingly engaged in the world of work. Therefore, the family with a dependent person must face health expenses to ensure that caregivers or nurses assist. Long-term care comprises a complex of medical, nursing, rehabilitation, and social assistance services that involve high management costs, whether they are provided in hospitals or nursing homes. The alternative can be represented by an efficient home assistance service [1]. The progress of detection technologies, integrated systems, wireless communication technology, nanotechnologies allows the creation of intelligent systems for continuous monitoring of human activities, even without hospitalization, ensuring more efficient and effective integrated home care services with cost containment to sustain.

2. TECHNOLOGIES

The specific application scenarios where Information and Communication Technologies (ICT) can be helpful include: automatic and remote localization and tracking of the patient, the exact knowledge of the location of patients is useful in case of urgent assistance; patients status monitoring, depending on the specific pathology, different information on patient status may need to be collected to be able to detect any abnormal change in their values. We can use other technologies to cope with the care of the elderly. Moreover, we can integrate them through suitable algorithms that improve their performance by ensuring a continuous health monitoring system. These systems allow not only to alert those in charge in sudden events but also to predict the risk of disease onset; moreover, they can improve the quality of life and safety of the elderly through the management of existing conditions.

An aged care system involves different aspects such as:

- monitoring of physical activities;

- real-time monitoring of vital signs;

- precise positioning.

The system will feature different technologies for acquiring the data classes relating to the activities mentioned above. A software system is also needed to process the data, extract the features and develop the recognition process.

A graphic representation of the human activity recognition (HAR) system is shown in Fig. 1

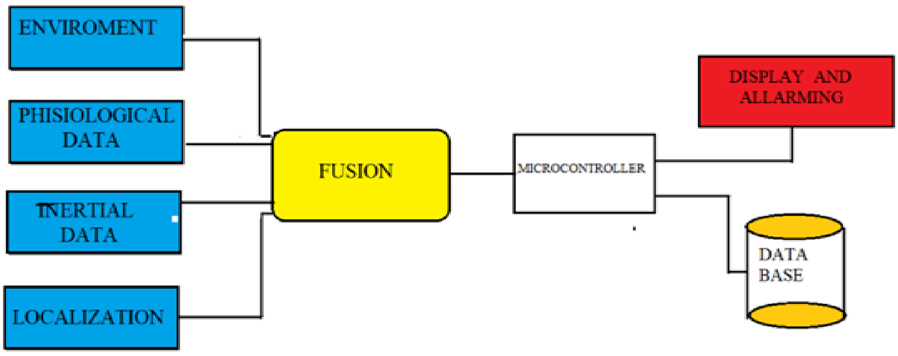


Fig. 1. Human activity recognition (HAR) System

2.1. Sensors

Depending on the task of monitoring, many different types of sensors are used. The data are collected and transmitted to a microcontroller to process and analyze. Based on the data processed on the current physiological state of patients, it can produce an alert message for caregivers in case of abnormal values. The data can be sent to a PC to be stored and displayed in graphical and numerical form.

Wearable technologies provide significant help in the development of aged care systems [2]. Smart watches, smartphones, and smart clothing all come with features that help capture information about the health of the elderly. Each has limitations that force the integration of different devices to have all the information needed to recognize the activities carried out, identify the home's position accurately, and monitor vital signs in real-time. Smartphones, for example, are suitable for detecting some actions carried out by the elderly but do not allow the detection of vital signs unless they integrate with other devices placed in direct contact with the skin. Smart watches allow in part to acquire these vital signs but have limited constraints on the quantity and location of sensors. The so-called intelligent clothing can provide the solution to these problems to install a series of sensors. These devices can communicate with smartphones to process biometric information such as heart rate, temperature, breathing, stress, movement, acceleration [3]. However, they cannot trace a precise position and are impractical from the point of view of freedom of movement. Continuous detection and monitoring of elderly activities are the focal points for the care system. Not only it detects abnormal situations, but it can reduce the effects of sudden negative events. Two different technologies can be used for the recognition of human activities:

- recognition based on vision [4];

- sensor-based recognition [5].

Vision-based systems require integrated cameras and sensors. This solution is expensive since cameras have to be installed in all places frequented by the elderly. Furthermore, the accuracy of recognition is affected by the lighting of the rooms and by inevitable visual disturbances.

Due to these factors, the sensor-based system is preferred to the above system. For the characteristics presented by the sensors based on micro-electro-mechanical systems (MEMS) technology, the HAR system has proved more suitable for remote monitoring of the elderly [6]. These systems have several advantages that make them more suitable. The advances made in MEMS manufacturing techniques have made these devices cheaper, very small, and have low power consumption. Above all, they do not produce negative effects on patients' health especially due to electromagnetic phenomena. For elderly care, the system should monitor normal activities such as standing, sitting, walking, climbing, and descending stairs and detect abnormal situations such as falls, fainting, chest pains, and changes in body temperature. The positioning of the sensor and the choice of different sensors are important elements to identify different actions. For example, the data obtainable from the gyroscope are better for recognizing the activities of ascent and descent of the stairs. In contrast, activities such as standing or sitting are better recognized through the data obtainable from the accelerometer. They are used to measure acceleration along a sensitive axis and for particular frequency ranges. They are very effective for detecting unsolved behaviors of the subject, such as not getting out of bed, no relevant activity for a given time interval, or changes in routine activities. We collect data for body movement analysis [7], the postural orientation of a subject [8], or fall detection [9]. The detection of this event is crucial as a delay in providing the appropriate treatment can lead to serious complications. Different accelerometers are based on different transduction principles, such as piezoelectric, piezoresistive, or capacitive. HAR systems cannot rely exclusively on accelerometers. They are not suitable for complex scenarios, so they are integrated with additional sensors such as gyroscopes, magnetometers, physiological parameters detectors, and environmental sensors, improving the accuracy in recognizing the activities.

Body temperature is one of the detectable physiological parameters and is an essential element in ascertaining the health of the elderly. We can use a variation of it to highlight symptoms of stress that can alter the health conditions of the elderly [10]. The standard core body temperature at rest and in good condition usually is around 37 degrees Celsius. Body temperature varies according to the metabolic rate, which is lowest in the morning because the body has rested and is higher at night. The body is affected by the muscular activity carried out during the day. The sensors used to monitor body temperature are thermistors, but there are also devices based on thermoelectric or optical devices.

The heartbeat represents another detectable physiological parameter indicative of the physiological state of the subject. Heart rate variability (HRV) represents the change in the period of consecutive heartbeats in a person, reflecting their physical state that modulates heart rhythm. HRV indicates current heart-related abnormalities, and we can diagnose certain cardiovascular diseases through its measurement [11]. The heart rate in a healthy and resting subject varies between 60 and 100 beats per minute. It can deviate from this reference value depending on the activity performed and on one's physiological state. Since the ECG signals are periodic, we can deduce the heart rate from the interval (RR) between one R wave and the next. Many complicated heart diseases such as arrhythmia, myocardial ischemia, and Long QT Syndrome are diagnosed using the HRV signals [12].

Recent work has shown that the EMG signal associated with accelerometric signs can improve monitoring accuracy [13]. The EMG signal is detected with electrodes placed on the surface of the skin, acquiring the values of the electric potentials generated by the contraction of the muscles. It is instrumental in examining people's fitness level; however, the signal is altered by the presence of motion artifacts, so by associating them with those derived from a triaxial accelerometer, reasonable compensation can be obtained.

2.2. Localization

As part of an integrated aged care system, it is necessary to monitor the people as they move within the home or outside the building. In this case, we speak of knowing their exact positioning. This information implies an accurate localization method to correct where to direct the necessary help in accidents and sudden illness. Localization, in general, refers to that process of determining the place where an object is located, which can be static or mobile. In the case of a stationary object, the system will decide only once. Otherwise, in the case of a moving object or subject, it will be necessary to continuously determine in real-time its position within a physical space that can be a hospital or one's home. In this case, we also speak of tracking. The two terms, localization and monitoring, are intimately connected in the sensor system to monitor their physical conditions and decide their needs. Current positioning technologies can be divided into two categories: external and internal positioning systems. In outdoor environments, several well-established navigation systems can provide localization with an accuracy of about 1m. Many of these navigation systems use GPS (Global Positioning System) [14] and GLONASS (Global Navigation Satellite System); however, the accuracy of these satellite-based systems decreases dramatically for satellite signal losses due to obstacles in the presence of walls and time lag issues. Therefore, these positioning technologies are not suitable for closed environments where people spend much of their time.

2.3. WSN

In recent years, numerous internal positioning systems (IPS) have been developed, including various hardware platforms, communication protocols, and location algorithms [15]. The monitoring and tracking activities use sensors capable of communicating with each other and network infrastructures called WSN (Wireless Sensor Network). The WSN is made by sensors node to gather cooperation, limited processing, and data transmission of monitored patients to the remote center using a wireless channel [16]. To make all this function, the WSN needs a particular node that can wirelessly communicate and be placed in different points within the area to be monitored. The components of a WSN are the target node, sensor node, and sink node. These nodes must have the following features: small size, low power, cheap, intelligent, multifunctional, and wireless interface to communicate with others. The WSN can be of two types according to the dislocation of sensor nodes: 1) structured network when the nodes are arranged in a predetermined manner, 2) unstructured when many nodes are placed randomly. According to the application, the components of sensor nodes are assembled in a single PCB (Printed Circuit Board) or more PCB. A WSN must have these characteristics [17]:

• **Distribution**: The nodes can be placed in a not predefined location making the network dynamic.

• **System lifetime**: Lifetime depends on a battery. To supply power to the network, it needs to use some precautions: secondary energy, data aggregation, short transmission range, multi-hop routing.

• **Cooperation**: The limited processing ability and memory of sensor nodes require that they interact so that, from their aggregation, there is an efficient processing capability [18].

• **Localization**: Since each node interacts with its neighbors, it must know its position and localization of its neighbors to the processing and cooperation.

It must be adopted a localization technique to identify the positions of nodes [19]. From a conceptual point of view, a human indoor localization and tracking system is typically constituted by a reference node, called a beacon or anchor, which sends a ranging request to an unknown mobile device attached to the target. Once the mobile node has received the signal, it responds by sending, in turn, an acknowledgment signal. In this way, the system can calculate the transmission time between the fixed node and the mobile node. This time is then sent to a calculation center. Appropriate positioning algorithms allow the identification of the exact position of the target [19]. The entire localization process can be divided into two steps: measuring some node metrics that need to be localized. The next is represented by the algorithm used to calculate the position [20].

***Measurement techniques**

The metrics used are distance, angle, and connectivity.

 # Techniques based on the distances between a node and an anchor (known node):

- ToA

- TDoA

- RSS

- TOF

 # Technique based on the angle of reception:

- AoA.

 # Technique based on connectivity

- Radio hop count

*Positioning Technique**

The positioning technique compute the location of unknown nodes based on measured metrics and can be [21]:

-Lateration

-Multilateration

-Angulation

2.4. Communication

Another determining element on the accuracy of the localization system is represented by the communication platform used on the WSN network. There are several techniques, but the most used are RFID, WI-FI, UWB, BLE, and VLP. For elderly care scenarios, the accuracy must be between 0.5m and 1m; the update rate cannot be less than 0.5s [22].

RFID, which uses radio signals to track people and objects automatically, includes two parts readers and tags. In general, the tags can be classified into active and passive. Passives gather energy from the radio waves of a nearby RFID reader, while active ones have their local power source and can be read from up to hundreds of meters away from the reader [23].

WIFI is based on measuring the intensity of a WI-FI signal to obtain positioning. Four categories are distinguished as follows: RSSI, Fingerprint, AoA, TOF [24].

UWB is a technology capable of using external energy signals for short-range and wideband communications of the radio spectrum. The detection of the difference of arrival (TDoA) of an RF signal calculates the distance between a reference point and the target [25].

VLP is a positioning technique based on visible light communication that uses the light emitted by LEDs. These light signals are used to determine the position of an object or person in a room [26].

BLE is one of the most widespread technologies; it is a high-energy efficiency system based on transmitting signals from beacons to nearby mobile devices (tags) that determine the exact location (RSSI). This technology allows locating any mobile device [27].

2.5. Deep Learning

There are several techniques to measure motion characteristics during physical activities performed by a human subject. In particular sensor-based systems have recourse to inertial sensors (IMUs) such as accelerometers and gyroscopes to sample acceleration and angular velocity of the body [28]. Alternatively, the video-based system uses cameras to acquire images that characterize the activities carried out. For privacy issues in place cameras in personal space, we use a sensor-based system to monitor daily human activities.

One of the main problems is the representation of information. Activity Recognition is essentially a classification method. Therefore, it presents a common problem with all other classification systems that is ***feature extraction***. For sensor-based activity recognition, feature extraction is more difficult because there is a similarity between activities. It's challenging to produce features able to represent unambiguously the movement carried out. Composite activities represent another aspect that makes it challenging to recognize activities. Not all activities are characterized by simple actions but include a sequence of elementary steps. We can overcome this difficulty through data segmentation. Another aspect that makes the recognition activity complex is the presence of several actions carried out simultaneously by the same subject or the concomitance of several subjects in the same environment. To improve the accuracy of the system, the technique of data segmentation can be used. The evolution of technologies based on Deep Learning (DL) algorithms has proved very effective in indoor localization, estimating spatial and temporal coordinates, and the other information connected with the type of activity. The ability to classify signals and the process of extracting significant characteristics from the acquired data are effectively carried out by Deep Learning models [29]. The structural architecture of the DL models made up of multiple layers gives them a high ability to learn the descriptive characteristics from complex data, favoring the ability to analyze multi-sensory data, which translates into a higher degree of accuracy in the phase of recognition [30].

Since one of the most favorable advantages of deep learning technology is the impressive power of automatic feature learning, using a neural network allows one to realize this goal. Convolutional Neural Network (CNN), which represents a branch of the Deep Neural Network (DNN), has provided excellent results for complex image classification tasks [31].

2.5.1. Convolutional Neural Network

Convolutional neural networks (CNN) process data through many layers of artificial neurons. This process of the human brain (CNN) is constituted by a set of different layers that act as extractors of the features of the input images and a fully connected terminal network that acts as a classifier. It has proved to be an effective solution for image recognition. They are built to analyze images included within certain data sets and to classify objects in images within them. CNN is a network composed of several convolutional layers [32]. Each processing layer comprises a convolutional filter, an activation function (ReLu), a pooling function, and a fully connected layer. At the end of each processing step, an input is generated for the next layer. In the convolutional operations, the set of trained filters is convolved with input images to extract the specific feature to create the feature map, which becomes the input for the next filter. The design of a CNN network requires a training period followed by a test phase. During the training phase, the images are labeled and transferred to the subsequent layers to allow the structure to convert from the representation level of the original input to a higher level and more abstract representation to constitute the reference feature maps with which the network must compare the output feature maps. Once the training and test phase of the network has been completed, we will determine the survey's accuracy level.

Each layer comprises three levels: Convolution, ReLu, and Pooling.

- Convolutional Level (**CONV**) is the main level of the network. Its objective is to identify patterns. They are multiple, and each of them is designed to identify features present in the initial image. Each layer learns the ability to extract specific parts of the photos placed at its entrance. Multiple layers in cascade combine the features of the previous layers with higher programmed extraction levels.

- Rectified Linear Unit (**ReLu**) Level is placed after the convolutional level and can cancel negative values obtained in the previous classes.

- Pool level allows identifying if the study characteristic is present in the previous story. The pooling layer obtains images with a particular resolution at the input and returns the same number of pictures with fewer pixels.

The result of the convolution operations is the production of feature maps obtained with the help of filters that are matrices containing proper values for finding specific characteristics in the input images.

At the end of the sequence of convolutional layers, there is then the fully connected level (**FC**) which aims to establish the identifying classes obtained in the previous levels according to a certain probability.

Each category represents a possible answer that the system will most likely choose. During the recognition phase, the network performs a classification operation to identify which class the input image belongs to, identifying the one with the highest probability. The values of the filters are initially chosen randomly. They are subsequently improved at each iteration of the process during the training phase. With the loss function, it is estimated that the model's predictions are plausible; in practice, the discrepancy between actual values and predicted values is measured. The error is subsequently processed using the stochastic gradient technique. It is a cyclical technique consisting of two phases:

* forward propagation;

* updating the gradient value.

After the propagation phase, the outputs produced, compared with the expected ones, determine the prediction error. This error is used to calculate the gradient of the loss function, which is then propagated backward in the network (backpropagation). The gradient descent algorithm uses these values to update the assigned weights to minimize the loss function value.

3. BACKGROUND

Below is a brief overview of the state of the art of solutions adopted. There are multiple jobs with hardware and software platforms for patient monitoring, localization, and tracking. Some of the most significant and representative of the different approaches used are recalled here.

As part of the HAR wearable system, the study presented by Yan and al. is interesting in which an approach called "Adaptic Accelerometer-based Activity Recognition (A3R)" is proposed. It is based on acquiring data from a mobile phone, considering a fixed sampling and varying frequency and characteristics in real-time, an energy saving of 50% can be obtained [33]. It has been tried furthermore by Bao et al. [34]. The performance of a HAR model depends on the number of accelerometers and the position of the applied sensors. Park et al. [35] proposed a new approach for solving the problems related to the Human-Activity Recognition (HAR) and the Energy Expenditure (EE). Their technique involved the use of an ECG and an accelerometer. They designed a database comprising of 6 different human activities (like standing, sitting, resting, walking, ascending, and running) performed by 13 volunteers. Their findings indicated that the use of human physiological data, obtained by wearable sensors, significantly impacted both HAR and EE estimation, which are crucial functions in the mobile healthcare system. Bayat et al. [36] developed a HAR system using a smartphone triaxial accelerometer and considering various daily activities. They designed a digital low pass filter to isolate the acceleration component of gravity. They used different classifiers to evaluate the recognition performance. They found that using probability averaging as the fusion method could achieve an accuracy rate of 91.15%. Classifications of data obtained by accelerometer and gyroscope of smartphones have been focused on in different studies. Bulbul et al. [37] have developed research-based smartphone sensors using different machine learning classification approaches. Again, Ronao et al. [38] structured a convolutional neural network to recognize user activities by smartphone signals. Iqbal et al. [39] have created an Internet of Things (IoT) platform based on a web application that integrates wearable sensors, smartphones, and activity recognition. The smartphone collects the data from inertial sensors and sends it to the server to recognize the physical activity. The data are represented in feature vectors used to train and test supervised machine learning algorithms for activity recognition. Several studies have been developed regarding the physiological parameters, but the researchers paid attention to blood pressure (BP) and body temperature monitoring. For BP, one method applied is pulse transit time (PTT) [40]. The interval between the peak of the R-wave in electrocardiogram (ECG) and the fingertip photoplethysmogram (PPG) is related to arterial stiffness. It can estimate systolic blood pressure (SBP) and diastolic blood pressure (DBP). Another method is the ultrasound that measures the arterial diameter waveform along with the local PTT (in the form of pulse wave velocity) and then applies the Bramwell-Hill equation to compute the absolute pulse pressure (systolic BP-diastolic BP) [41]. The other method is arterial tonometry is a long-standing method [42]. In theory, this method can measure a BP waveform without using a cuff by pressing a force sensor on an artery. The sensor must flatten or applanate the artery so that its wall tension is perpendicular to the probe. However, manual and automatic applanations have proven difficult, so the measured waveform is routinely calibrated with cuff BP values in practice. The measurement acquired with this method requires calibration with cuff BP values. The measurement of core body temperature can be related to skin temperature. Niedermann et al. [43] have developed an algorithm to predict body temperature using skin temperature measured from the chest. However, the equipment highly professional was not suitable for continuous monitoring and long term. Lately, Woo et al. [44] have used a patch-type device that put on the skin over the clavicle measured humidity and skin temperature from which they predicted the body temperature. With an algorithm, they studied the relationship between perspiration rate and skin temperature to predict the body temperature; the error committed makes the method unreliable. Wei et al. [45] instead referred to a measurement system of body temperature based on a wireless semiconductor sensor. The device is placed on the back under the neck because there is a thin layer of fat and muscle on this skin area, ensuring skin temperature measurement close to the body temperature. The wireless health monitoring system comprises two parts: a wireless temperature measuring device attached to the back of the body and a receiver device to acquire data and send it to a computer for display and recording.

The technologies frequently applied for internal localization were infrared, radiofrequency, and ultrasound. Bahl et al. [46] have created a radio-frequency system called RADAR. It works by processing signal intensity information at different base stations to provide overlapping coverage in the area of interest. To give people's location, it merges measurements with the signal propagation model. RADAR uses signal intensity information gathered at multiple receiver locations to triangulate the patient's coordinates. Ni et al. [47] developed a system called LANDMARK. It is a localization system to enhance the accuracy location by using RFID tags and RFID readers to locate patients. It depends on the power level of tags and the relation between power level and RSS readings. It requires a further location tag by comparing the RSS of the nodes with those of reference tags. The RFID readers send the tag information to a central server with the readers' ID and power level. Priyantha et al. [48] with their CRICKET system have privately created a platform in which they have privileged the recognition location rather than location-tracking. It identifies the location of mobile and anchor nodes by analyzing information generated by the anchor node. Each anchor generates two signals: RF and ultrasound (US), employed to locate the mobile node by applying the technique TDoA to determine their distance from anchor nodes. Then an inference algorithm is used to determine the area in which the node is located. Baunach et al. [49] developed a system based on ultrasonic for tracking mobile objects with the TDoA measuring technique. In this system, mobile objects are equipped with a sensor carrying an ultrasonic transmitter. At the same time, anchor nodes are provided ultrasonic receivers and radio transceivers positioned on both nodes for time synchronization and data transmission. The position of the mobile object is determined with the multilateration technique.

With application based on the light-sensitive sensor, we can measure either distance or angle of the object to be located [50]. It is a system of localization and tracking of a device-free object using light sensors. Each sensor is equipped with one light sensor and one transceiver to communicate with each other forming a connected WSN. For object tracking, the system applies a probabilistic method. The monitored area is divided into cells, to each cell is assigned a probability. The cell with the highest chance is associated with the position of the moving object. One of the main aspects to be taken into account on sensor-based HAR is the information representation. Traditional classification methods are based on the features that must be extracted from kinetic signals. Often this feature extraction process is not very accurate [51]. The solutions based on deep learning (DL) were very efficient for estimating the position coordinates and the room and floor identification. They are structured in two main phases: data preparation and pre-processing carried out in off-line mode and the other of task prediction performed online [52]. Several applications have been developed based on different DL models. Mishra et al. [53] through the use of a smartphone, acquired data on human activities via accelerometer and gyroscope. With the help of a Deep Neural Network (DNN), they have recognized the activities, achieving an accuracy of 97.3%, confirming the suitability of this technique compared to traditional learning techniques. Murad et al. [54] proposed using long short-term memory (LSTM) based deep recurrent neural networks (DRNNs) to build HAR models for classifying activities mapped from variable-length input sequences. They developed architectures based on deep layers of unidirectional and bidirectional RNNs. The models are then tested on various benchmark datasets to validate their performance and generalizability for an extensive range of activity recognition tasks. Bevilacqua et al. again [55] use a convolutional neural network (CNN) to classify human activities. Raw data are obtained from a range of inertial sensors. Different combinations of activities and sensors are explored. The results obtained confirm the validity of the use of motion signals inserted in different architectures of CNN networks for the identification of physical activities.

4. SYSTEM DESIGN

The proposed system is made of instruments that enable the caregivers to operate on time and ensure efficient performance in the whole process of the healthcare system. The functional scheme is shown in Fig. 2.

It differs from other solutions adopted for the following innovative aspects:

- Recognition system that fuses three types of information on patient location and human motion to identify the activities usually carried out in a closed environment; the data source is an accelerometer, gyroscope, physiological data, and patient location.
- CNN (Convolutional Neural Network) is used to survey location and activity.
- VR (Virtual Reality) we can use it for neural network and training optimization. Since the data to be collected and labeled for the localization of each node is an essential step for training and the data processing for each physical location must be interpreted by the CNN network to be appropriately converted into image maps.

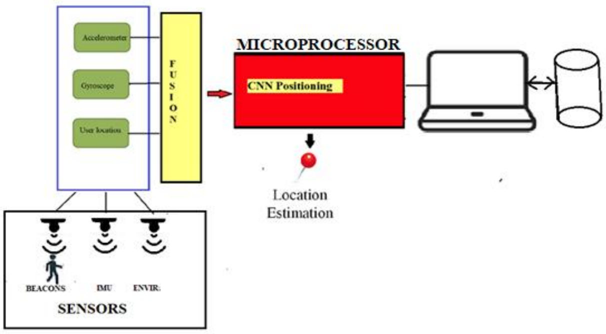


Fig. 2. Functional diagram of the system

4.1 Fusion

The microprocessor chosen for this application has a MotionFX library, a component of the middleware library of the X-CUBE-MEMS1 software of ST Microelectronics that provides a real-time fusion of motion sensor data and also performs gyroscope polarization and complex iron calibration of the magnetometer. Each of the sensors integrated into the microprocessor includes information regarding the orientation. The gyroscope provides the variations of direction through the integration of angular velocities; the accelerometer and the magnetometer instead provide information on the movement through the projections of the components of the vector acceleration of gravity and Earth's magnetic field in the reference system considered. This information taken individually is not reliable. The gyroscope data can shift, and this affects the orientation estimate; we can overcome this problem by using the magnetometer to provide complete orientation information. Likewise, the magnetometer does not have a very high bandwidth and suffers from magnetic disturbances, but this can be compensated with a gyroscope. Therefore, a sensor fusion algorithm for 3D orientation estimation in space is used to provide absolute orientation data, particularly a digital filter based on Kalman theory, to fuse data from different sensors and compensate for the limitations of individual sensors. The package acquires data from the accelerometer, gyroscope (6-axis fusion), and magnetometer (9-axis fusion). It provides real-time motion-sensor data fusion to provide absolute values on orientation in 3D space, including direction (i., e., direction of magnetic north).

4.2 Structure

*T*he system has been developed considering an architecture consisting of three infrastructures, as shown in Fig.3. Smartphone connected via BLE to the microcontroller of STMicroelectronics about the infrastructure for data collection from the sensors. Through the Android BLE Sensor application, the data collected are attributed to the activities of patients in terms of acceleration, pedometer, jogging, downstairs, upstairs, gyroscope, and environmental data in terms of temperature, pressure, and humidity. These data are then integrated with heart rate and location data

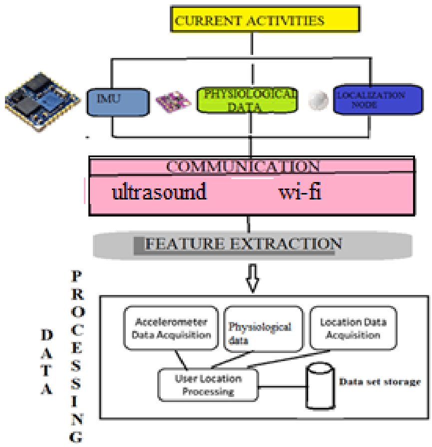


Fig. 3. System Architecture

4.3 Microcontroller

The core of the system is represented by the STM32L475 microcontroller ultra-low-power STM32L4 Series MCUs based on Arm® Cortex®-M4 core (Fig. 4) with 1 Mbyte of Flash memory and 128 Kbytes of SRAM, in LQFP100 package whose main characteristics are represented by:

• Reconfigurability

• Multisensor detection

• IMU and Mobile Node Integrated

• Bluetooth® V4.1 module (SPBTLE-RF)

• Sub-GHz (868 MHz or 915 MHz) low-power-programmable RF module (SPSGRF-868 or SPSGRF-915)

•Wi-Fi® module from Inventek Systems (ISM43362-M3G-L44)

• Dynamic NFC tag based on M24SR with its printed NFC antenna

• 2 digital omnidirectional microphone (MP34DT01)

• Capacitive digital sensor for relative humidity and temperature (HTS221)

• High-performance 3-axis magnetometer (LIS3MDL)

• 3D accelerometer and 3D gyroscope (LSM6DSL)

• 260-1260 hPa absolute digital output barometer (LPS22HB)

• Time-of-Flight and gesture-detection sensor (VL53L0X)

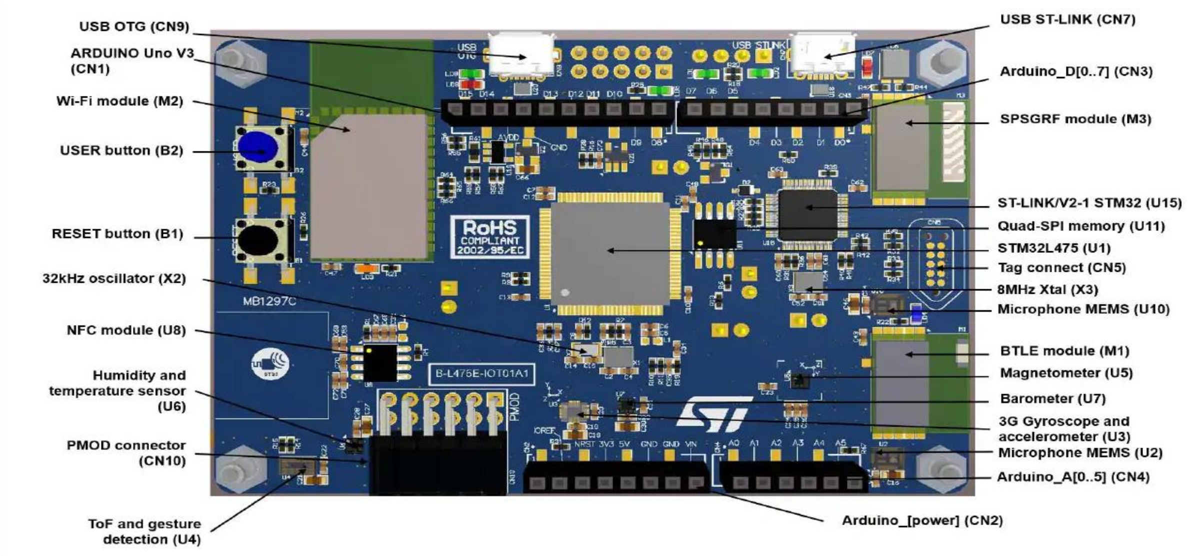


Fig. 4. Layout of STM32L475

4.4 Localization

The localization network, made by sensor nodes able to communicate, is based on wireless infrastructure and targets localizing the moving people within a closed environment. The platform is based on ultrasonic technology, characterized by a fixed infrastructure and some mobile units. It uses an RF time synchronization between emitters and receivers, ultrasonic chirp signal for TOF and distance estimation, and sphere intersection for point coordinate calculation [56]. The calculation algorithm is based on a two-steps process. In the first, the distances between the fixed points and the moving unit are measured. In the second, these distances geometrically determine the position of the moving team within the reference system defined by the placement of the anchors. Distances are measured using ultrasonic signals and are based on calculating the so-called flight time (TOF). The time elapsed from the moment the signal is transmitted at the time of its arrival to the receiver. The accuracy of the measurement depends on the accuracy of time measurement. We must ensure perfect synchronization between the times of the transmitters and those of the receiver. Just think that a sync difference of 1 μs is results in uncertainty about the distance of about 0.343mm. Among the calculation, the technique applied is multilateration, based on the intersection of the traced spheres with a radius equal to the distances between mobile units and beacons and centered each of them at beacon points. The network consists of four anchor nodes or beacons (NA) that can communicate wirelessly and be placed at different points within the area to be monitored. They were placed at the corners of a square placed on the ceiling of the rooms. With this arrangement, it was possible to use a closed-form solution of the intersection of only three spheres, which correspond to three transmitters.

The fourth emitter serves to determine the measurements' validity and decrease the localization error through the average. The ANT protocol is applied for signal transmission, differentiating it from other protocols usually used to enable devices to communicate concurrently without interfering with each other, low speed, and reduced consumption. Signal detection starts with the activation of the master unit that, through the synchronization signal, enables beacons (NA) to transmit to the mobile unit (MU). The connection between the master unit and the beacon MUs is via ANT. The control unit emits ultrasonic chirp signals sequentially through the four beacons. Each MU receives ultrasonic signals and calculates its position. Communication between the master unit and PC is only used to transfer positioning data. MUs can operate autonomously as MUs GPS. Experimental positioning uncertainty is less than 14 mm. The functional scheme of the system is shown in Fig. 5.

The system consists of the master unit, one or more mobile units and four anchors, and a central unit whose characteristics are shown below.

The master unit consists of an N5 module (Dynastream Innovations, Cochrane, Alberta, Canada) connected to a PC via UART/USB interface. The N5 includes a chip nRF51422 (Nordic Semiconductor ASA, Oslo, Norway), equipped with a 16-MHz ARM Cortex M0 processor and radio supporting 2.4-GHz communication protocols ANT [23] or Bluetooth smart.

The mobile unit is equipped with a D52 module (Dynastream Innovations, Cochrane, AB, Canada) built around the nRF52832 chip (Nordic Semiconductor ASA, Oslo, Norway). It includes a 12-bit ADC set at 200 kSamples/s and features a 64-MHz ARM Cortex M4, powered by a 3.7-V 30×17×5 mm3 rechargeable lithium-ion battery with a capacity of 250 mAh.

The control unit comprises an N5 module and a microcontroller PIC16F1704 (Microchip Technology Inc., Chandler, AZ, USA) for the ultrasonic chirp storage and output through the built-in 8-bit DAC. A linear up-chirp in the bandwidth of 30–50 kHz is employed. The ultrasonic transducers are Series 7000 Electrostatic Transducer (SensComp Inc., Livonia, MI, USA).

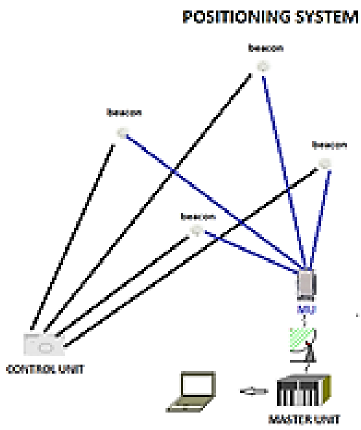


Fig. 5. Positioning functional flow

4.5 CNN

CNN network serves for the recognition phase. It is a network mainly used as a supervised learning algorithm and can learn how to classify images from a sample dataset.

It is based on the principle of the convolution filter applied to the pixel matrix that composes the image. The kernel applied sequentially to the image can highlight the fundamental characteristics of the image and, in this way, produce essential data for the classification of the image itself.

A Keras model allows building the CNN network. For CNN design and its training, we applied HAR_IGN_WISDM trained on the public Wireless Sensor Data Mining (WISDN) dataset in Jennifer R. Kwapisz et al. t. [57].

The dataset contains six daily activities collected in a controlled laboratory environment. The activities include jogging, walking, ascending stairs, descending stairs, sitting, and standing. The data is collected from 36 users using smartphones in their pockets with the 20Hz sampling rate (20 values pers.).

The activities detected are:

* Downstairs

* Upstairs

* Sitting

* Standing

* Walking

In Keras, it's taken Sequential model that consists of a linear stack of levels.

Through the use of FP, extension STM32Cube AI integrated into STM32AI; the neural network was created and subsequently imported to the microprocessor Fig.6.

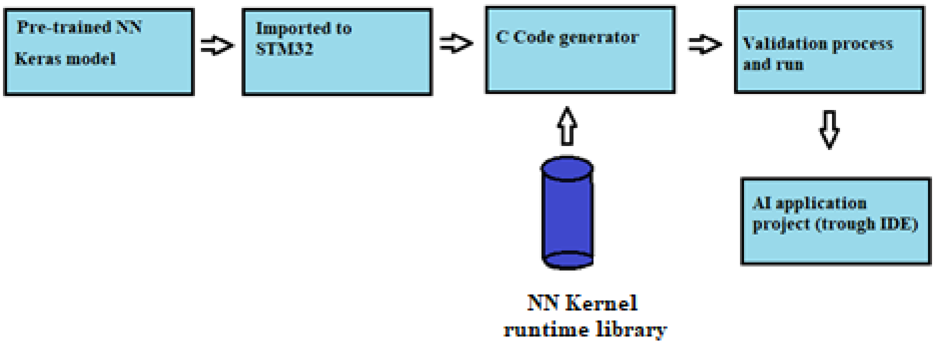


Fig. 6. Flow-chart of neural network creation and conversion on MPU for compilation and run

It consists of two convolutional layers, three Relu layers, two pooling layers, and two fully connected layers whose layout is shown in Fig.7. A good design of the neural network involves the right compromise between the number of intermediate layers and the processing time; increasing the number of layers also increases processing time.

The convolutional layers have 32 filters; Kernel size =2.

Downstream of the Max pooling, a Dropout layer is placed to regularize and avoid the fitting, followed by a flatten layer. Two hundred fifty-six outputs characterize the first fully connected layer while the second has 128 outputs; pooling window size = 2; dropout = 0.2.

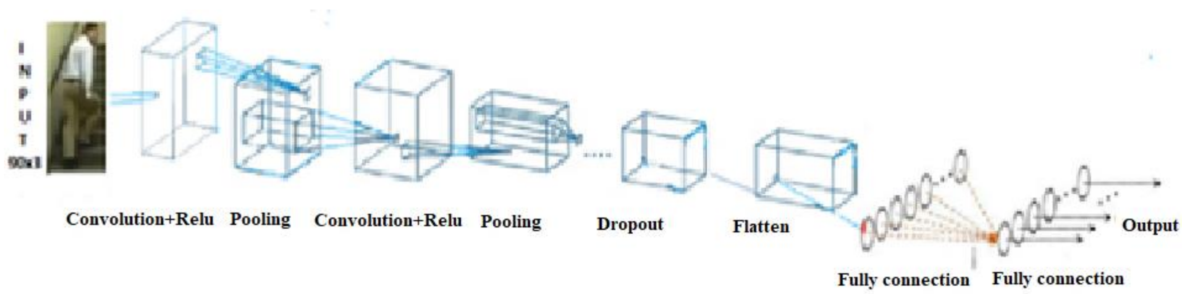


Fig. 7. CNN configuration

4.6 VR

To improve the recognition phase of the neural network, we can use the two fundamental characteristics of virtual reality: immersion and interactivity. Virtual reality can create an environment in which each subject simulates the usual movements. Through the immersion function, the subject is projected directly into the real world. With interactivity, the subject can interact with the virtual world. We can transfer activities data to a virtual model to verify the correct interpretation. We can use the Unity platform (2019) to create the virtual reality environment; through it, the enhancement phase of the neural network previously created with the STMicroelectronics AI module STM32 was performed. We must transfer the pre-trained Keras model into VR specifying the sequence of the layers; with activities data provided, the system verifies the accuracy of prediction. In case of unsatisfactory results, the neural network training process can proceed until optimal precision is achieved (Fig.8).

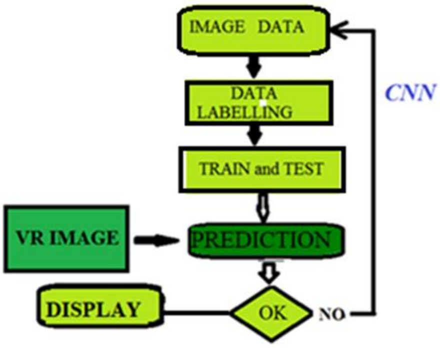


Fig. 8. VR System for CNN optimization

5. RESULTS

Through the SW in the Function Pack AI SENSING1 of STM32Cube, it was possible to connect the STM32L475 board to a smartphone via BLE and use an Android STBLE Sensor application to configure the device and to visualize the data transmitted via BLE by sensors. The smartphone used was ALCATEL mod.5024D_EEA.

Through this application, we acquire the different human activities and audio signals of the scene with subsequent classification based on the data generated by the neural network implemented on the same microcontroller.

MEMS devices have detected the following characteristics through the BLE platform: Temperature, Pressure, Humidity, and Data motion (Accelerometer, Gyroscope, Magnetometer). Environmental data are sent every 50 ms and displayed on the device display when connected to the board, as shown in Fig. 9.

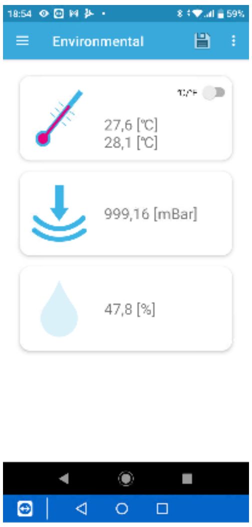


Fig. 9. Environmental data

Inertial data are sent every 50 ms, and the relative recognized activities are shown on the device. Through the function plot of the smartphone, it is possible to graphically represent all the values of data motion (Fig.10).

a) b) c)

Fig. 10. Data motion a) Accelerometer b) Magnetometer c) Gyroscope

The human activity recognition algorithm (HAR) based on motion sensors and one Acoustic Scene Classification (ASC) is HAR_IGN_WSDM trained on the public Wireless Sensor Data Mining (WISDM) dataset.

For human activity recognition, a high pass filter (4th order, cutoff frequency around 1 Hz) separates the gravity component from the dynamic (oscillating) part of the acceleration. The active element of gravity is rotated to always point in the same direction regardless of the sensor's orientation. Rodrigues's rotation formula is used to turn the active part. The Activity Recognition page on display can monitor the AI neural network classification results from the HAR_IGN_WSDM algorithm.

The page shows one of the following recognized activities:

• stationary

• walking

• jogging

• stairs

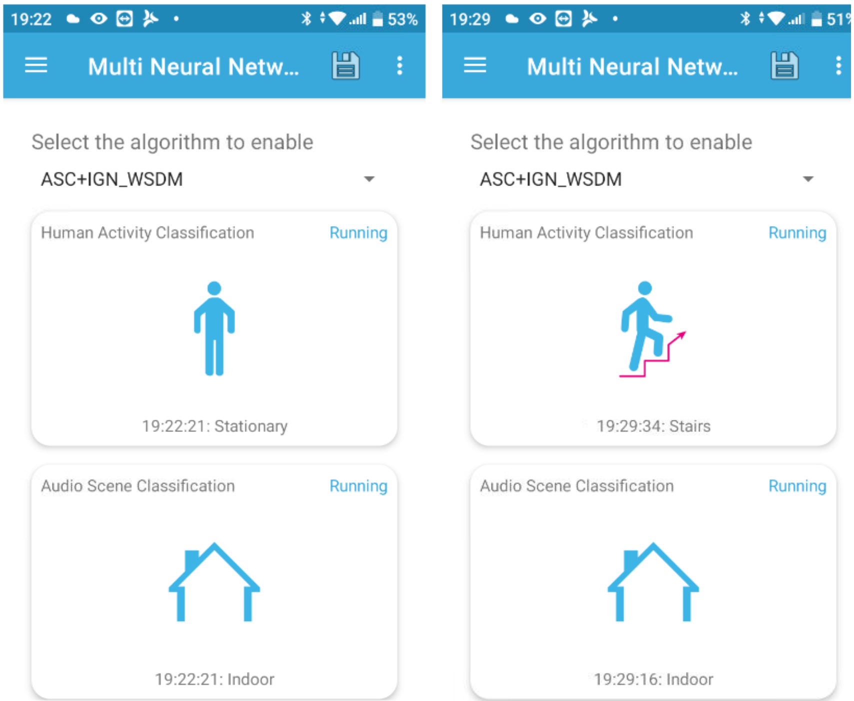


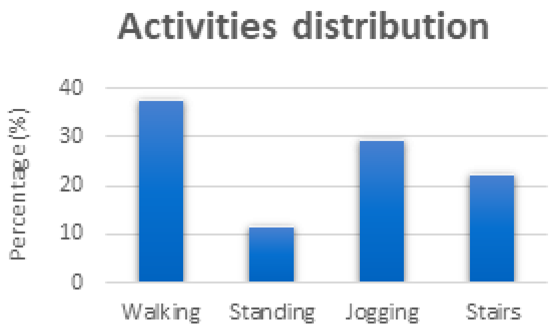
Fig.11. Example of recognized activity (stationary, stairs)

Since the algorithm must collect data before recognizing any activity, all images appear grayed out first for some seconds to turn blue then once the recognition phase has begun (Fig.11).

6. DISCUSSION

In this article, we focused attention on recognizing activity by detecting the actions performed by users. This detection can be done using different sensors. Still, our choice instead was to apply a smartphone that is rich in high-end hardware and features that can be used by any user and do not require the subject to wear additional sensors that can prevent their activities. Another relevant aspect is the potential of this choice which arises from the opportunity to equip a device accessible from an economic point of view and easy to use. For our purpose, we have chosen to monitor walking, running, sitting, standing, upstairs, downstairs. The STMicroelectronics STM32L475 microprocessor represents another relevant component of the system. In addition to multiway sensing and multilink communication, it has an internal STM32Programmer development environment that allows you to create, compile, and debug a project with STM32CubeIDE, facilitating the design of an integrated system like the one we hypothesized.

The data collected by users who used the smartphone while performing the various activities are represented in the following diagram showing the distribution of activity classes.



The data collected were grouped into four classes. Out of 1000 surveys carried out on the activities performed regularly by people daily, the highest percentages are for walking (37.2 %) and jogging (29.2 %). Most of these activities are characterized by repetitive movements, so we believe that this makes it easier to recognize them. Activities involving leg movement (walking, jogging, and alt) exhibit periodic behavior that the system can more accurately identify, are characterized by periodic peak acceleration values. Sitting and standing to exhibit no regular periodic behavior, and all acceleration values are relatively constant. The difference in the detection of these activities depends on the relative strength of the acceleration values. They turn for each axis by the different orientation of the device from the ground when the user is sitting or standing.

The following confusion matrix shows the results obtained from the prediction system adopted. The last column reports predictive accuracy values for each activity class. Precision values of more than 99 % were obtained for most types. The most difficult activities to identify are the ascent and descent of the stairs due to the confusion between the two movements. For simplicity of classification, we took into account the combination of the two. With the help of the localization system, it will be possible to understand if the activity connected with the stairs is related to the ascent or descent phase depending on where the last presence of the subject is detected, compared to the beginning of the survey.

Predicted values

Actual values

	Walking	Jogging	Stairs	Standing	Accuracy (%)
Walking	370	1	0	1	99,4
Jogging	2	289	1	0	98,9
Stairs	1	1	220	0	99
Standing	1	0	0	113	99,1

Table of the confusion matrix

The results obtained show that recognizing human activities obtained with the hypothesized system can be considered a highly accurate system for most properly-recognized activities at 99%. Greater accuracy is given by inserting the internal localization model into the system. Through this feature, the recognition of the activities carried out by the neural network is facilitated, and the identification of potentially dangerous situations is possible.

This solution was developed and tested in a simulated environment in the Laboratories of the University of Reggio Calabria. It was not possible to try it in a natural habitat for organizational reasons. The next step will be using the system with various types of users and in different environments that reproduce natural conditions present in the home or a nursing home.

CONCLUSION

An integrated system on an Android-based application on a smartphone and a microprocessor with an ultrasonic sensor network for monitoring and tracking subjects indoors was tested in the prototype presented. The data transmitted by smartphone to the microprocessor for the prediction can also identify abnormal situations or prompt interventions in an increased need for assistance. The system presented performances that are potentially comparable with the best existing solutions but with the advantage of representing a low-cost solution, with minimal energy consumption (3,4 μW) and easy expansion. The results obtained support the extension of the recognition of activities in authentic contexts. It will be possible to test the recognition of multiple aggregated activities and in different areas with diverse participants. Subsequent investigations will use other models for analysis of the recognition of activities.

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