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Sensor-based System for Monitoring of Child movements & falls

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Abstract: ***The rapid aging of the world's population, along with an increase in the prevalence of chronic illnesses and obesity, requires adaption and modification of current healthcare models. One such approach involves tele-health applications, many of which are based on sensor technologies for unobtrusive monitoring. Recent technological advances, in particular, involving micro-electro-mechanical systems, have resulted in miniaturized wearable devices that can be used for a range of applications. One of the leading areas for utilization of body-fixed sensors is the monitoring of human movement. This paper has presented the activity recognition method for children using only a tri-axial accelerometer and a barometric pressure sensor. Time-domain and frequency-domain features are extracted for categorizing body postures such as standing still and wiggling as well as locomotion such as toddling and crawling. In this approach, we use a single 3-axis accelerometer and a barometric pressure sensor worn on a waist of the body to prevent child accidents such as unintentional injuries at home. Labeled accelerometer data are collected from children of both sexes up to the age of 16 to 29 months. To recognize daily activities, mean, standard deviation, and slope of time-domain features are calculated over sliding windows. In addition, the FFT analysis is adopted to extract frequency-domain features of the aggregated data, and then energy and correlation of acceleration data are calculated. Child activities are classified into 11 daily activities which are wiggling, rolling, standing still, standing up, sitting down, walking, toddling, crawling, climbing up, climbing down, and stopping.***

Keywords: Activity recognition, Wearable sensors, Radio Frequency Identification System, Falls detection.

1. Introduction

HUMAN activity recognition is one of the most promising research topics for a variety of areas, including pervasive and mobile computing [1][2], surveillance-based security [3][4], context-aware computing and ambient assistive living. It has recently received growing attention attributing to the intensive thrusts from the latest technology development and application demands. Over the past decade sensor technologies, especially low-power, low-cost, high-capacity and miniaturized sensors, wired and wireless communication networks, and data processing techniques have made substantial progress. The advances and maturity of these supporting technologies have pushed the research focuses of the aforementioned areas to shift from low-level data collection and transmission towards high-level information integration, context processing and activity recognition and inference. At the same time, solutions for a number of real-world problems have become increasingly reliant on activity recognition. For example, surveillance and security try to make use of activity recognition technologies to address the threats of terrorists. Ambient assisted living aims to exploit activity monitoring, recognition and assistance to support independent living and ageing in place. Other emerging applications, such as intelligent meeting rooms and smart hospitals, are also dependent on activity recognition in order to provide multimodal interactions, proactive service provision, and context aware personalized activity assistance.

Activity recognition is a complex process that can be roughly characterized by four basic tasks. These tasks include (1) to choose and deploy appropriate sensors to objects and environments in order to monitor and capture a user's behavior along with the state change of the environment, (2) to collect, store and process perceived information through data analysis techniques and/or knowledge representation formalisms at appropriate levels of abstraction, (3) to create computational activity models in a way that allows software systems/agents to conduct reasoning and manipulation, and finally (4) to select or develop reasoning algorithms to infer activities from sensor data. For each individual task a raft of methods, technologies and tools are available for use. It is often the case that the selection of a method used for one task is dependent on the method of another task.

2. Classification of Activity Recognition:

2.1 Vision-based vs. Sensor-based activity recognition:

In terms of the type of sensor that is used for activity monitoring, activity recognition [5]-[7] can be generally classified into two categories. The first is referred to as vision-based activity recognition, which is based on the use of visual sensing facilities such as video cameras to monitor an actor's behavior and environmental changes. The generated sensor data are video sequences or digitized visual data. The approaches in this category exploit computer vision techniques, including feature extraction, structural modeling, movement segmentation, action extraction and movement tracking to analyze visual observations for pattern recognition. The second category is referred to as sensor-based activity recognition, which is based on the use of emerging sensor network technologies for activity monitoring. The generated sensor data from sensor-based monitoring are mainly time series of state changes and/or various parameter values that are usually processed through data fusion, probabilistic or statistical analysis methods and formal knowledge technologies for activity recognition. In these approaches, sensors can be attached to an actor under observation - namely wearable sensors or smart phones, or objects that constitute the activity environment - namely dense sensing. Wearable sensors often use inertial measurement units and RFID tags to gather an actor's behavioral information. This approach is effective for recognizing physical movements such as physical exercises. In contrast, dense sensing infers activities by monitoring human-object interactions through the usage of multiple multi-modal miniaturized sensors.

2.2 Data-driven vs. knowledge-driven activity recognition:

Though primitive activity data can be obtained through activity monitoring activity models are critical for interpreting the sensor data to infer activities. In particular, the mechanisms activities are recognized are closely related to the nature and representation of activity models. Generally speaking, activity models can be built using one of two methods. The first is to learn activity models from pre-existent large-scale datasets of users' behaviors using data mining and machine learning techniques. This method involves the creation of probabilistic or statistical activity models, followed by training and learning processes. As this method is driven by data, and the ensued activity inference is based on probabilistic or statistical classification, it is often referred to as data-driven or bottom-up approaches. The advantages of the data-driven approaches are the capabilities of handling uncertainty and temporal information. However, this method requires large datasets for training and learning, and suffers from the data scarcity or the "cold start" problem. It is also difficult to apply learnt activity models from one person to another. As such this method suffers from the problems of scalability and re-usability.

The other method for building activity models is to exploit rich prior knowledge in the domain of interest to construct activity models directly using knowledge engineering and management technologies. This usually involves knowledge acquisition, formal modeling, and representation. Activity models generated in this method are normally used for activity recognition or prediction through formal logical reasoning, e.g., deduction, induction or abduction. As such, this method is referred to as knowledge-driven or top-down approach. Knowledge-driven approaches have the advantages of being semantically clear, logically elegant and easy to get started. But they are weak in handling uncertainty and temporal information and the models could be viewed as static and incomplete.

Vision-based activity recognition has been a research focus for a long period of time due to its important role in areas such as surveillance, robot learning and anti-terrorist security. Researchers have used a wide variety of modalities, such as a single or multi-camera, stereo and infra-red, to investigate a diversity of application scenarios, for single or groups of individuals. Several survey papers about vision-based activity recognition have been published over the years. Aggarwal and Cai discuss the three important sub-problems of an action recognition system—extraction of human body structure from images, tracking across frames, and action recognition. Cedras and Shah present a survey on motion-based approaches to recognition as opposed to structure-based approaches. Gavrila and Poppe present surveys mainly on tracking human movement via 2D or 3D models and the enabled action recognition techniques. Moeslund et al. presents a survey of problems and approaches in human motion capture, tracking, pose estimation, and activity recognition. Yilmaz et al.and Weinland et al.present surveys of tracking objects for action recognition.

Compared to the number of surveys in vision-based activity recognition, and considering the wealth of literature in sensor-based activity recognition, there is a lack of extensive review on the state of the art of sensor-based activity recognition. This may be because the approach only recently became feasible when the sensing technologies matured to be realistically deployable in terms of the underpinning communication infrastructure, costs and sizes. Given the rising population and the potential of the approach in a wide range of application domains, a systematic survey of existing work will be of high scientific value. It will inform researchers and developers in related communities of the current status and best practices and to signpost future directions. This survey is intended to present an in-depth comprehensive overview on the latest development of sensor-based activity recognition. It will cover the lifecycle of the approach, and provide descriptions and comparisons of various approaches and methods from which strengths and weaknesses are highlighted.

3. Types of Wearable Ambulatory Sensors:

The study of human motion and falls employs many techniques, including visual observations, video capture, interviews, diaries, questionnaires, physical measurements, and wearable ambulatory sensors. Self-report tools are simple to administer, but capture partial information and suffer from inherent bias due to inaccurate recall, whether intentional or not. Objective measurements use a variety of physical tools such as force plates, gait mats, and balance testing apparatus. Such tests are designed to be conducted in a clinical setting, usually in dedicated gait and falls clinics, and are relatively costly and inappropriate for long-term monitoring of large patient cohorts under real-life conditions [8]. Miniature sensors or sensor systems that can be worn on the body offer another means of gathering physical activity and falls data in a way that is suitable for clinical settings but has immense potential for long-term use, especially in the community [9].

3.1 Accelerometers

Accelerometers are used to measure acceleration along a sensitive axis and over a particular range of frequencies. Since they measure acceleration due to gravity and movement, the actual component of movement-related acceleration needs to be separated from the gravitational. The gravitational component is nevertheless useful in defining a subject's postural orientation. There are several types of accelerometers available based on piezoelectric, piezoresistive, or variable capacitance methods of transduction. They all employ the same principle of operation of a mass that responds to acceleration by causing a spring or an equivalent component to stretch or compress proportionally to the measured acceleration (Hooke's law). Early available accelerometer sensor devices were of a uniaxial design; however, further advances in MEMS technology have lead to the availability, at low-cost, of biaxial and tri-axial devices, with their sensitive axes mounted orthogonally to one another. Vibrating gyroscopes measure angular velocity by taking advantage of the Coriolis Effect. MEMS-based gyroscopes use a small vibrating mass within the sensor that undergoes a slight displacement when the gyroscope is rotated. If measured over time, a change of angle in relation to an initial known angle can be detected. These sensors have known limitations, which include output drift over time, output offsets when the device is stationary, and a sensitivity which is limited to a particular range of angular velocities.

3.2 Magnetometers

Magnetometers can be used to measure the orientation of a body segment in relation to the earth's magnetic north, utilizing electromagnetic induction. In order to work effectively, the orientation of the sensitive axis of the device must be aligned with the magnetic field lines; composite devices containing multiple devices on orthogonal axes are now used to compensate for this requirement.

3.3 Goniometers

Goniometers are fairly rudimentary devices, based on a potentiometric element which is attached to a joint's rotation point to measure joint angle, although more advanced flexible electro-goniometers employ strain gauge elements. These sensors (along with *inclinometers* that are used to measure the slope of an object with respect to gravity using an artificial horizon) are mainly employed in the determination of the range of motion of human body joints.

3.4 Sole pressure sensors

Sole pressure sensors assess the pressure distribution across the planter aspect of the foot by measuring the net ground reaction force. These are often realized using resistive or capacitive-based strain gauges. Such pressure sensors have been incorporated into socks for increased ergonomics.

3.5 Pedometers

Pedometers, also called step counters, detect human motion and, using specialized software, translate the measurement into a count of the number of steps performed. In the past, pedometers were based on mechanical switches or pendulums, but nowadays they incorporate MEMS sensors, typically accelerometers.

3.6 Actometers

Actometers are usually attached to an individual's extremities in order to measure the magnitude of mechanically produced movements. These sensors are basically a modified version of the mechanism in a self-winding mechanical wrist watch, where the self-winding rotor responds to movement by driving the minute hand. The resulting output is a measurement of "actometer units" per known time period; this enables an estimation of total energy expenditure. In the context of clinical ambulatory monitoring, it seems that the most commonly used WAMs consist of accelerometers, gyroscopes, or both. Integrated systems that employ accelerometry with a gyroscope and a barometric pressure sensor (for measuring elevation) or a magnetometer have also been explored.

4. Radio-frequency identification System

This system describes the design and testing of a prototype sensor-enabled radio-frequency identification (RFID) system, which consists of RFID tags paired with proximity and movement sensors for monitoring arm activity. In this system, movement sensors (i.e., accelerometers) are affixed to objects, along with one component of a RF proximity sensor. The other component of the RF proximity sensor is connected to an active RFID tag and worn on the arm of interest. Manipulation of instrumented objects with that arm produces synchronous signals from the movement and proximity sensors, permitting tracking of which objects are handled, when handling takes place, and whether handling is by the person and arm of interest. The proposed technology, thus, collects much richer objective data than possible with accelerometers or other physical activity monitors.

RFID systems consist of small tags that transmit a unique ID using RF when interrogated by the RF reader that monitors the status of these tags [10]–[11]. Software on a PC connected to the reader processes the RFID signals. "Passive" RFID tags transmit their ID when they encounter the reader's radio waves [11], whereas "active" RFID tags, which are battery powered, transmit their ID independently from as far as 85 m. Applications involve tracking whether tagged objects are within the range of the reader or not. Examples of commercial applications are monitoring when hospital equipment or patients leave designated areas or monitoring changes in inventory of merchandise in a warehouse [12].However, RFID systems have not been used to remotely monitor upper-extremity activity in stroke survivors or other rehabilitation populations.

5. Proposed System

Using Multisensors and GSM communication monitoring children activity at home. Multi sensors are used to monitor daily life children at home. This approach is trained using manually annotated data and applied for activity recognition. A waist- worn sensor could fail to detect activities involving head motion, body tilt, and hand motion. Multiple sensors are used to improve the robustness of the systems and increase the reliability of the high-level decision making. Using RFID prevents children to go danger areas like electrical socket, RFID is used to trace the movement and existence of goods. RFID can provide a direct and continuing recognition, including the identification, position, and trace of children. Implementation of vision-based activity recognition, which is based on the use of visual sensing facilities such as video cameras to monitor an actor's behavior and environmental changes.

The proposed system consists of four main components: 1) the wearable sensor node to measure movement and height from the ground by using a 3-axis accelerometer and a pressure sensor; 2) the wireless receiver to receive the measured data over Nordic wireless protocol and transmit it to PC over USB connection; 3) the activity monitor and analyzer working on the PC to aggregate the measured raw data and to analyze behavioral characteristics using features and classifiers; and 4) the speaker to broadcast emergency alerts to their parents or a guardian. The proposed activity recognition method using a 3-axis accelerometer and a pressure sensor comprises the following three steps: 1) collecting and preprocessing the sensor data from an accelerometer; 2) extracting features; and 3) training and classification. In order to process, we have to remove the noise with a moving-average filter because errors made in the early steps may increase the classification error and the uncertainty on each further step. After preprocessing the sensors signals, it is necessary to choose the adequate features which we take as time-domain and frequency-domain features.

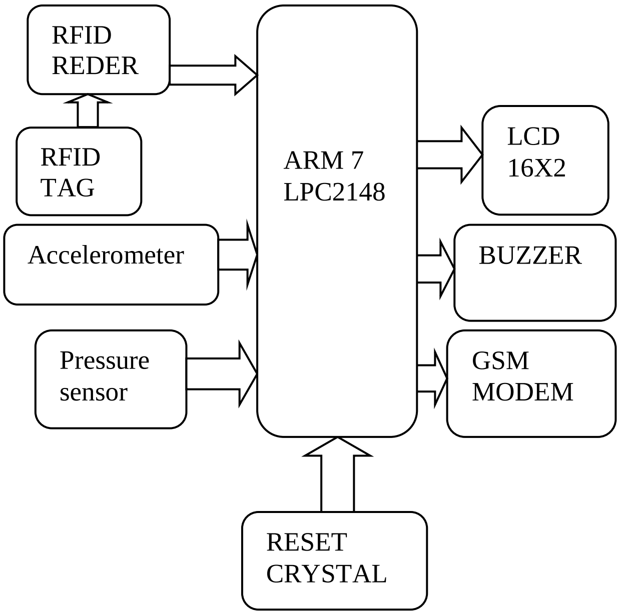

Figure 1. Block diagram of System Architecture

ARM7 is the heart of the system which controls all the blocks of the system shown in the figure 1. To observe the child and to show all the activities of the child in home, accelerometer and RFID card (NFC Cards) are attached. Where accelerometer detects child present and falling stages through its axis and RFID card will be read by RFID reader. Which will acts as near field communication RFID card is attached to table or bulky items. Buzzer will be used which acts as an alarm and it is used to make sound when child come towards harmful objects. GSM is used for getting message to their parents/guardians for take care, where the parents/guardians mobile consists of application to graph the child activities. The SONAR(Sound navigation & ranging) is used in this system to detect the bulky or huge materials in front of child and voice output will comes in android mobile.

5.1 Acccelerometer

ADXL335 is a complete 3-axis acceleration measurement system. The ADXL335 uses a single structure for showing the X, Y, and Z axes. As a result, the three axes' shows directions. They are highly orthogonal and have little cross-axis sensitivity.

5.2 RFID

Radio-frequency identification (RFID) is an automatic identification method. RFID tags or transponders are used to store and retrieve data. The technology requires some extent of cooperation of an RFID reader and an RFID tag. An RFID tag can be used for identification and tracking purpose using radio waves RFID tag can be applied or incorporated into a products, animals, or peoples. Some tags can be read from several meters away and beyond the line of sight of the reader.

5.3 Buzzer

A piezo buzzer is driven by square waves (V p-p). A piezo buzzer can make higher SPL with higher capacitance, but it consumes more electricity. The sound output is measured by decibel meter. Applying voltage and square waves, and the distance of 10 cm. A buzzer can make sound on any frequencies, keep working well between -30℃ and +70℃.

5.4 ARM7

1. It is 32 bit and single port device IC voltage will vary from 1.8 to 3.3v.
2. Low power consumption.
3. 12v power supply.
4. 12 Mhz provided by crystal oscillator.

5.5 GSM

Global system for mobile communication (GSM) is a globally accepted standard for digital cellular communication. GSM has established in 1982 is the name of a standardization group to create a common European mobile telephone standard. AT Commands are used to get information in SIM card.

5.6 LCD (Liquid Crystal Display)

LCD is a thin and flat electronic visual display. A liquid crystal display uses the light modulating properties of Liquid Crystals (LCs). LCs does not emit light directly. LCD is a 2 line display each line consists of 16 pins. It has the operating voltage is 5v. LCDs uses very low power than the Cathode-Ray Tube (CRT) counterparts. LCDs use only atmosphere light to illuminate the display because they are ruminative. Even displays that do consume much less power than CRT devices require an external light source (i.e. computer displays).

When setup is powered up, it initializes LCD, ADC, UART. Configure the ADC to read the data of sensors. The obtained ADC values are compared with reference values. If the obtained values are less than reference value then activity of child will be recognized. The activity of child can be extracted by swiping the RFID tag. When RFID is swiped the unique ID is sent to the controller. By processing the ID, the activity of child is displayed on LCD and also the records are sent to their parents via GSM.

6. Conclusion

Activity recognition has become the determinant to the success of the new wave of context-aware personalized applications in a number of emerging computing areas, e.g., pervasive computing and smart environments. We present a survey of the state-of-the-art research on sensor-based activity recognition. The activity recognition method for children using only accelerometer and pressure sensor. To improve the performance of the child activity recognition method, six features including magnitude, mean, standard deviation, slope, energy, and correlation are extracted from the preprocessed signals. Multiple feature sets are compared to find an optimized classification method, and showed how well they performed on a body. Our proposed method including the pressure information demonstrated an improved performance in detecting climbing up and down activities. Results showed that using a barometric pressure sensor could reduce the incidence of false alarms. The early warning system will give the parents enough time to save their babies, and, thus, minimize any instances of falling accidents or sudden infant death syndrome.

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