Enviado: 18/09/2022 *Recibido: 27/09/2022* *Aceptado: 07/11/2022*

UNIVERSIDAD DISTRITAL FRANCISCO JOSE DE CALDAS

VISIÓN ELECTRÓNICA

https://doi.org/10.14483/issn.2248-4728

VISIÓN ELECTRÓNICA

State of the art on technological trends for the analysis of behavior and human activities

Revisión del estado del arte sobre tendencias tecnológicas para el análisis del comportamiento y actividades humanas

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Abstract

The study of human behavior allows the knowledge about people's behaviors, behavior determined by multiple factors: cultural, social, psychological, genetic, religious, among others, which affect the relationships and interaction with the environment. The infinity of data in our lives and the search for behavioral patterns from that data has been an amazing work whose benefit is focused on the determined patterns and intelligent analysis that lead to new knowledge. A significant amount of resources from pattern recognition in human activities and daily life has had greater dominance in the management of mobility, health and wellness. The current paper presents a review of technologies for human behavior analysis and use as tools for diagnosis, assistance, for interaction in intelligent environments and assisted robotics applications. The main scope is to give an overview of the technological advances in the analysis of human behavior, activities of daily living and mobility, and the benefits obtained.

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Cite this article as: F. O. Ovalles-Pabón, “State of the art on technological trends for the analysis of behavior and human activities”, Visión Electrónica, vol. 16, no. 2, 2022.

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Keywords: Human Activity Recognition, human behavior, sensors.

Resumen

El estudio del comportamiento humano permite el conocimiento sobre las conductas de las personas, conducta determinada por múltiples factores: culturales, sociales, psicológicos, genéticos, religiosos, entre otros; que inciden en las relaciones y la interacción con el entorno. La infinidad de datos en nuestras vidas y la búsqueda de patrones de comportamiento a partir de esos datos ha sido un trabajo asombroso cuyo provecho se centra en los patrones determinados y el análisis inteligente que conducen a nuevos conocimientos. Una cantidad significativa de recursos a partir del reconocimiento de patrones en las actividades humanas yde vida diaria ha tenido mayor dominio en la gestión de la movilidad, la salud y bienestar.

El actual documento presenta una revisión de las tecnologías para el análisis del comportamiento humano y del uso como herramientas para el diagnóstico, asistencia, para la interacción en ambientes inteligentes y aplicaciones de robótica asistida. El alcance principal es dar una visión general de los avances tecnológicos en el análisis del comportamiento humano, actividades de la vida diaria y movilidad, y de los beneficios obtenidos.

Palabras clave: Reconocimiento de actividades humanas, comportamiento humano, sensores.

1. Introduction

Human Activity Recognition (HAR) consists of predicting the physical activity of a person based on their recorded behavior or movement, the movements can be normal movements such as walking, standing, sitting, climbing stairs. Human activity recognition has become a very popular field of research, the goal is to assign an activity category to the signal provided by sources to create applications for improvement in different fields. HAR includes applications ranging from medical, sports, ambient intelligence to entertainment applications [1-2] The different sources of data used in the detection of human activities depend on the application, traditionally the discrimination of activity was performed by multimedia resources such as images or videos [3-4] by analyzing image sequences, then research incorporated portable sensors housed in the body of study or in the environment [5-6] and with the recent emergence of ubiquity and the Internet of Things (IoT - Internet of Things) has made use of sensors embedded in different devices [7-8]

The development of the present work is to present the contributions made to date, to know the different technologies available from the recognition of human activities based on different sensors that lead to improvements in various fields of application.

The article is structured as follows: unit 2 defines the research done on Human Activity Recognition, the modality of obtaining information and recognition methods, section 3 explores various applications and the conclusions are described in section 4.

2. Recognition of Human Activities

The recognition of human activities involves the exploration of human activities in order to discover a corresponding pattern in their development, it is a technique that can be applied to many real-life problems and is human-centered. So far research is based on the recognition of simple human tasks, making recognition in complex activities represents a challenge in the area of research [9] The nature of human activities poses the challenges of recognizing activity and discovering activity patterns; recognition can be done by a predefined conceptual model and from sensor data without predefined assumptions. Therefore, in HAR research, an activity data acquisition system is first built and then data analysis to discover activity patterns [1]

2.1. Modality of procurement systems

To create a human activity recognition system researchers have prototyped systems that use acceleration, audio, video and other sensors to recognize user activity. Generally speaking HAR can be in two forms: camera-captured video-based and sensor-based [10-11]

Computer vision research (when analyzing images or videos) can be described as the temporal evolution in space of different body postures. Early research focused on activity recognition of video sequences using color cameras [12-13] However, there was considerable loss of information when capturing articulated human movement with monocular video sensors, a possible solution is to capture stereo data from multiple views and reconstruct the information in 3D [14], the use of cameras that allow capturing color and depth information have been used as beneficial devices as they reduce the variations made by ambient light [15]

Numerous works have demonstrated the recognition of human activity using data from sensors such as accelerometers, gyroscopes, proximity sensors, vital sign sensors and GPS, as they are not only less privacy invasive alternatives to visual systems, but have also been the most popular and widely used, especially from commonly used devices such as smartphones and various body-worn accessories such as watches, bands, glasses and helmets [16-17], the combination of various data sensor modalities can improve activity recognition, data such as heart rate and temperature along with acceleration can detect physical intensity [18], acceleration and angular velocity are modified as a function of human speed in body movements, widely have been used accelerometers located in multiple locations on the body [19-20-21] With the versatility that has acquired the use of the smartphone numerous studies take advantage of models that offer embedded multimodal sensors and require little structure to operate [22-23-24], the first studies worked offline and the data obtained were processed and classified offline currently the recognition of activities is performed by combining measurements of portable sensors with supervised learning algorithms and defined architectures [25]

2.2. Recognition methods

The objective of classification is the categorization of the obtained information, probabilistically the classification action is defined as a calculation of the activity, several classifier algorithms have had much popularity, the difference for the selection are the obtained results, besides considering the capabilities of the processing platform, as memory and response time are important factors to take into account. Some researchers generate the classification model on a workstation [26-27] other researchers can implement them on smartphones [28]

The most popular algorithms for generating classification models are: Decision Trees [29], K-NNs K-nearest neighbors, Naïve Bayes, Hidden Markov Models (HMMs), Support Vector Machine (SVM), Gaussian Mixture Models (GMMs) [30-31-32] Adapted methods have also been used as they represent a reduction in computational cost while maintaining the same accuracy compared to traditional methods [22]

With traditional methods progress has been made in pattern recognition however not in all cases they are able to achieve satisfactory results, a limitation found is that features are extracted by heuristic methods based on human experience and some statistical information can be inferred in the recognition of high level activities, such as drinking coffee with respect to a low level activity such as walking [33] Implementing deep learning for HAR with different types of the networks allows defining features learned automatically through the network instead of being designed manually. In addition, the deep neural network can also extract a high-level representation which makes it more suitable for complex activity recognition tasks [34]

3. Applications

There are many possible applications that can be developed from the recognition of human activities and many fields that can be explored, among them are:

3.1. Video surveillance

Visual monitoring and video surveillance despite having the disadvantage of requiring expensive hardware has attracted the attention of the community due to the increase in demand for security resulting in intelligent surveillance [32-33-34], researches use HAR for law enforcement verification, others study gait recognition for personal identification, and analyze behavior to ensure security in shopping malls, hospitals, bridges among others [35]

3.2. Sports

As for sports applications are used to recognize the sports activities done daily [36], others make calculations of energy expended by sports activity performed [37], some devices allow to make training history and can monitor group activities such as cycling [38]

In martial arts, sequences of movements are detected for educational systems and video games [39], and there are also applications that help children learn Kung Fu [40-41]

3.3. Home assistance

It consists of smart home applications that facilitate and enable residential control by the inhabitants [42], others incorporate assistance service by measuring vital signs offering emergency help [43]

3.4. Health

It is the area that has diversified the most as it includes disease diagnosis, health care, care for children and the elderly. The PAMAP consists of a physical activity and heart rate monitor [44], for remote monitoring MEDIC offers health care services for movement and fall detection [45] In rehabilitation, the effect of medication on Parkinson's patients is investigated [46], in patients with rheumatoid arthritis, abilities and disabilities are evaluated [47] Recent proposals propose robotic assistance in adult care [48], the detection of falls before impact [52] constitutes an interesting aid in adult care, for children it facilitates monitoring under treatment or by diagnosis [50] In chronic disease management there is the possibility of monitoring sports activity to manage the disease for example in patients with chronic lung disease, others provide feedback for better management of their condition [54-55] Intelligent health system is the most explored field with the greatest use of activity recognition.

The recognition of emotions also aims to give an assessment of the patient's well-being and his or her interaction with the environment, allowing an understanding of the health-comfort relationship [31-56]

4. Conclusions

It can be defined that in the medical field there is a greater diversification of advanced applications based on Human Activity Recognition, specifically health and wellness applications that seek to improve the living conditions of patients with chronic diseases, children and adults, likewise it is important to highlight that applications in the sports field monitor performance and facilitate the management of sports activity. Particular interest has been awakened in surveillance applications that seek to ensure the security implemented through intelligent surveillance.

However, the selection of the traditional pattern-based recognition method, deep learning or an adaptation of them makes a difference in obtaining the results.

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