User Indoor Localisation System enhances Activity Recognition: A Proof of Concept

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Abstract. Older people would like to live independently in their home as long as possible. They want to reduce the risk of domestic accidents because of polypharmacy, physical weakness and other mental illnesses, which could increase the risks of domestic accidents (i.e. a fall). Changes in the behaviour of healthy older people could be correlated with cognitive disorders; consequently, early intervention could delay the deterioration of the disease. Over the last few years, activity recognition systems have been developed to support the management of senior citizens' daily life. In this context, this paper aims to go beyond the state-of-the-art presenting a proof of concept where information on body movement, vital signs and user's indoor locations are aggregated to improve the activity recognition task. The presented system has been tested in a realistic environment with three users in order to assess the feasibility of the proposed method. These results encouraged the use of this approach in activity recognition applications; indeed, the overall accuracy values, amongst others, are satisfactory increased (+2.67% DT, +7.39% SVM, +147.37% NN).

Keywords: Activity Recognition, User Indoor Localisation, Independent Living, Wearable Sensors.

1 Introduction

One of the main challenges of AAL is to provide socially sustainable home care services for senior citizens and to reduce the caregiver's work burden, thus increasing their quality of work.

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Older people prefer to live independently in their home as long as possible. In particular, they want to reduce the risk of domestic accidents because of polypharmacy, physical weakness and other cognitive disorders which can increase the risks of accidents (i.e. a fall). Sometimes, cognitive decline is associated with the onset of difficulties with transportation, cooking, medication, management, and prospective memory tasks like remembering appointments and grocery lists [1].

Literature evidence underlines how ICT technology can help to prevent a decline in the quality of life and support senior citizens during daily activities [2]. In particular, information on which type of activity and how users spend their time at home could prevent the deterioration of cognitive disorders, support the management of their life and lead to target interventions from family and caregivers [3].

The rise of mobile phones, the Internet of Things and smart devices has facilitated the process of measuring individual activities and his/her surroundings. However, most AAL applications require more than the simple collection of measurements from a variable of interest: they require complex algorithms and sometimes a huge set of sensors involved. In this context, accurate information on the user's activity and behaviour represents one of the main challenges of pervasive computing in AAL fields [4]. Users with cognitive disorders (i.e. dementia, Alzheimer's disease) could be monitored to prevent undesirable consequences [5]. In this sense, changes in the behaviour of healthy older people could be correlated with cognitive disorders; in this sense, an early intervention could delay the complications of the cognitive disorders [6].

The first scientific work on activity recognition systems dates back to the late 1990s [7]. However, there are still many challenges and motivations that will stimulate research in this field [8]. Some of these challenges mainly regard the selection of sensors and, consequently, the choice of attributes to measure. It is also important to design a portable, unobtrusive and inexpensive data acquisition system. Additionally, due to the complex and real operative conditions, it is worth mentioning that it is essential to find an optimal balance between the type of intrusive sensors used, the measured attributes, the complexity of the algorithm, and the system accuracy.

In this context, we focus on the use of wearable sensors in order to measure attributes related to the body movement (using an accelerometer), physiological signal (using an electrocardiogram – ECG) and user's location inside the home in order to improve the accuracy of the activity recognition system.

1.1 Related Works

Analysing the state-of-the-art, according to Lara et al. [4] it is evident that activity recognition systems can be based mainly on two different approaches. In the first approach, i.e. "*external*", the sensors are placed on a fixed point of interest, and the information on the activity depends on the voluntary interaction of the user. The second approach envisages the use of "*wearable*" sensors placed on the human body. This type of sensor could provide information on four groups of categories: environmental context, body movement, user location and physiological signal.

1.1.1 External Sensors

This first approach envisages the use of "*external sensors*"; smart homes and cameras.

Over the last few years, Smart Home systems [9-10] have been developed in order to support senior citizens improve their home safety. Recently, commercial IoT solutions [11-12], have been commercialised to provide service of home remote monitoring. The idea behind this kind of system is to measure the user's interaction with everyday objects to understand their behaviour and activities. However, the accuracy and precision of the activity recognition systems depend on the number of sensors installed in the environment and on the target objects with which the user has to interact [13–15].

Cameras are mainly used for security and surveillance tasks. They are used for posture and gesture recognition, as well as the localisation of multiple users in indoor environments. People detection can be performed by detecting faces or human bodies, while more complex processing is needed to distinguish different users. Nevertheless, there are some issues regarding privacy, pervasiveness and complexity of video process that could limit the use of camera systems [16]. Over the last few years, user indoor localisation systems based on cameras have been developed; so these systems are considered as too invasive and too complex [17-18]. For instance, Zhu et al. [19] present an activity recognition system that fuses together information on user location and human motion. However, they use the Vicon[2] motion capture system to estimate the user's location, which is not easy to install in a real house. Within the Robot-Era project, a user localisation system based on a sensor fusion approach was implemented, exploiting both range-free and range-based localisation methods [20].

1.1.2 Wearable Sensors

[2] Vicon Motion Capture; official website: http://www.vicon.com/

The second approach includes the use of "*wearable sensors,*" which could provide information on human movement, physiological signal, context and user location.

Human movement can be estimated by means of inertial sensors. For instance, tri-axial accelerometers, gyroscopes and magnetometers are the most broadly used sensors to recognise daily activity. They are used to estimate indoor and outdoor atomic actions (like walking, lying, descending/ascending stairs) [4], human gestures [21], and fall detection [22]. A recent study has highlighted how an accelerometer placed on a smartphone and smartwatches could be used to estimate daily activity, avoiding forcing the user to wear external sensors [23].

Vital sign data (i.e. heart rate, respiration rate, skin temperature, skin conductivity) could provide information on the user's physiological status and performed activity [24-25].

Other research groups have investigated how different typologies of wearable sensors could be fused to improve the efficacy of recognition tasks. For instance, Pärkkä et al. [26] aggregated a total of 22 signals including an accelerometer, vital signs and environmental sensors. Nevertheless, the presented system is very obtrusive because it requires a high number of sensors to be placed on the person. Lara et al. [27] present Centinela, a system that combines acceleration data with vital signs to achieve highly accurate activity recognition.

Mobile phones and portable devices are equipped with Global Positioning System (GPS), which represents a portable system that could provide information on the user's location, enhancing activity recognition tasks. This GPS system is able to locate the person in outdoor environments but does not work well in indoor environments.

1.2 Objective

In this context, this study aims to go beyond the state-of-the-art, presenting a proof of concept where information on body movement, vital signs and user's indoor location are aggregated to improve the activity recognition task (Fig. 1).

The presented solution includes two accelerometers placed on the human body: one on the chest and one on the lower back. These two positions are chosen because, in the future, these sensors could be integrated into "smart fashionable accessories" like a necklace or a fashion belt. Moreover, a commercial chest-bend monitors cardiac activity (electrocardiogram - ECG), and an unobtrusive user indoor localisation system provides information on the user's location [20].

In order to achieve the proposed goal, a strict methodology based on five main phases has been applied. The goal of this proof of concept is to demonstrate how information on user location can improve the recognition of eight common daily activities. Then, two different recognition models (with or without the information on user location) were built to compare the performance.

The remainder of the paper is organised as follows. Section 2 presents the methodology used in this work. Section 3 describes and discusses the results, while finally Section 4 concludes the paper.

2 Material and Methods

In this section, the methodology chosen for the data analysis is described in detail. It includes the experimental protocol definitions, a description of the experimental settings and the data analysis. The adopted methodology follows five main phases, which are listed below and described in detail in the following paragraphs:

Phase I: This phase includes the definition of the experimental protocol, the optimal choice of sensors and their software integration.

Phase II: This phase includes the preparation of the test-bed (Domocasa Lab), the recruitment of testers and the data acquisition according to the protocol defined in Phase I.

Phase III: This phase includes the preparation of data and the feature extraction for each participant. The included features were chosen according to the state-of-the-art and the aims of the paper.

Phase IV: In this phase, a classification analysis based on three supervised machine learning algorithms (viz. Decision Tree (DT), Support Vector Machine (SVM) and Neural Network (NN)) was conducted on two models to compare the results adequately.

Phase V: This phase includes the evaluation of the classification performed in the previous phase. A set of appropriate metrics was used to pursue this goal.

Matlab 2012a was used in Phases II– V to analyse the data offline.

2.1 Phase I: Experimental Protocol Definition

According to statistics [28], home is the most common place where European citizens stay during the day. In particular, among most common activities, European people (aged 20–74) spend 36% of their time sleeping, and 18% doing domestic work like preparing food or cleaning dishes. 22% of time is spent on activities related to free time, like watching TV (41%), resting on the sofa (4%) and reading books (4%). 10% is spent on activities related to gainful work and study (i.e. working at a PC).

Table 1. Experimental Protocol

Code	Time [min]	Activity	Location
SPC	3	Work at PC desk	Desktop PC
STV	3	Sit on sofa, watching TV	Sofa
LSO	3	Rest on sofa	Sofa
LS	3	Sleep in bed (supine)	Double Bedroom
LRS	3	Sleep in bed (on right side)	Double Bedroom
SK	3	Sit at kitchen table	Kitchen (near the table)
SB	3	Sit on toilet	Bathroom
CD	3	Wash up	Kitchen (near the sink)

Starting from these results, an experimental protocol has been defined. Eight daily activities were selected considering four main categories. (i) Work at PC desk, sit on sofa watching TV, and rest on sofa activities were chosen as the "free-time" category. (ii) Two different sleeping poses (supine and on the right side of the bed) were chosen for the "sleeping" category. (iii) Sit at the kitchen table and washing up were chosen for the "domestic work"; and (iv) sit on the WC represented the "personal hygiene" category (Table 1).

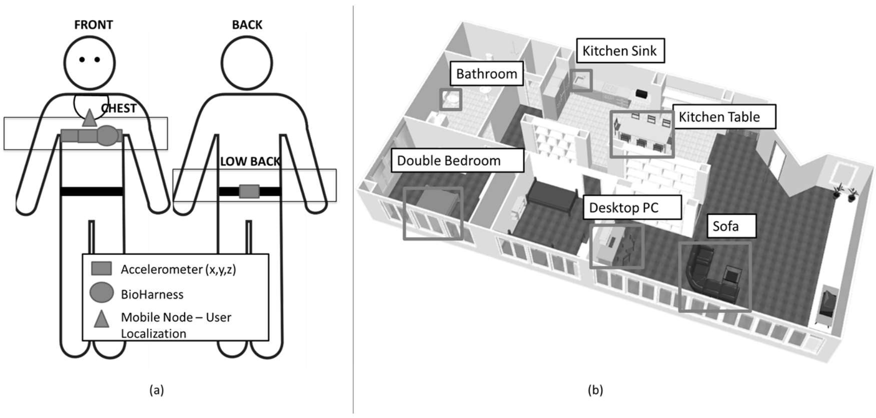

Figure 1. Proof of Concept Experimental Settings. (a) Wearable Sensor distribution on the human body; (b) Selected locations where the selected activities are performed.

These selected activities aimed to underline how user location could increase the accuracy of the activity recognition tasks. For instance, four different activities (SPC, STV, SK, and SB) presented equal “body orientation”; in fact, the user performed different activities while he/she sits in different places. Even the LS and LSO activities presented the same body orientation and similar physiological parameters, but were performed in two different rooms (Fig. 1b).

2.1.1 Instrumentation

The proposed system for daily activity recognition is shown in Fig. 2. It includes appropriate sensors to measure body acceleration, vital signs and the user’s location.

Hardware

The hardware agents included in this system were: wireless sensor networks to estimate the user’s location and two kinds of wearable sensors to estimate, respectively, the vital signs' and the user’s movement.

1. **Vital Signs** (ECG) were measured with a BioHarness Zephyr 3 chest strap, connected through Bluetooth to a computer. ECG was acquired at a frequency of 250 Hz.
2. **Body acceleration** was measured by means of two wireless 3-axial accelerometer sensors, one placed on the chest and the other placed on the lower back, as shown in Fig 1.a. The number of accelerometer sensors and their position were chosen according to literature evidence considering the balance between accuracy and the number of sensors. These sensors sent data through ZigBee protocol to a computer at a frequency of 50 Hz.
3. The **indoor user location** was estimated through a wireless sensor network, composed of a number of ZigBee wireless radio devices to estimate the user’s position with an in-room granularity, developed during the Robot-Era project [23,29]. This network was designed for the indoor user localisation, observing the Received Signal Strength (RSS) of the messages exchanged between the radios. It was composed of a ZigBee Coordinator (ZC), a Data Logger (DL), a wearable Mobile Node (MN) and a set of ZigBee Anchors (ZAs). The wearable MN periodically sent messages at 1 Hz to all ZAs within one communication hop. Each ZA computed the RSS as the ratio between the received and transmitted electromagnetic power on the received messages, and transmitted this value to the DL. ZAs were instrumented with 60° sectorial antennas and installed in a fixed position in the home environment. In particular, they were installed on walls and inside the furniture to

monitor the best accessed or interesting areas of the rooms, and to achieve an in-room localisation accuracy. The sectorial antennas were introduced to improve the signal-to-noise ratio of the RSS observations over the selected areas of interest for the user localisation. The MN was instead embedded an omnidirectional antenna for data transmission, to reduce the sensitivity of the localisation system to the user rotations. The DL node was connected to a PC via USB, to upload data for the processing. The entire localisation workspace was 200 m^2, covered by 17 anchors. The overall sensor density was approximately 0.1 device/m^2, but the density was higher in the most accessed areas like the kitchen (~0.23 device/m^2), bathroom (~0.25 device/m^2) and bedroom (~0.20 device/m^2). Additional details on these sensor networks are given in [29].

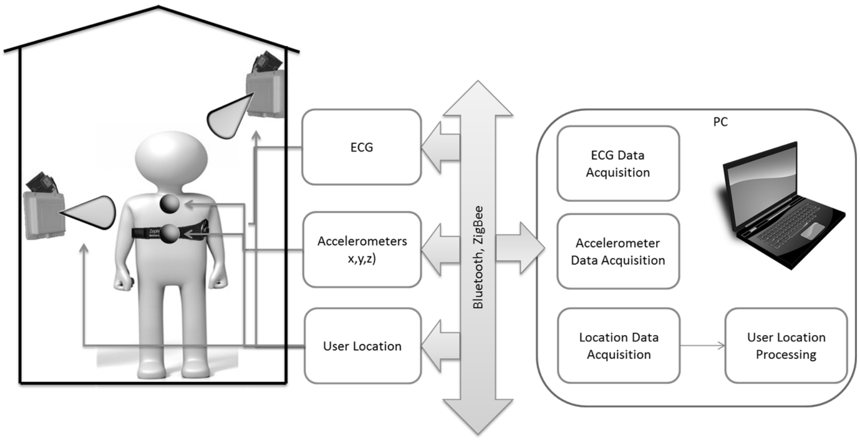

Figure 2. System architecture. The hardware part is composed of a BioHarness chest band, two accelerometers (red sphere), and the wireless sensor network to estimate the user's location. MN is represented by a green sphere. A computer collects all the information from these sensors through proper interfaces. Additionally, the user location processing module computes the user's location using the RSS signal.

Software

The software involved in this system includes four different modules developed with Visual Studio (Fig. 2). The ECG data acquisition was able to collect data from BioHarness, implemented using the SDK Zephyr developer kit. The second module was used to collect data from the accelerometers. The final two modules were implemented to collect RSS data from the DL and to compute the user's location with in-room granularity.

The user location processing module [30] was based on a sensor fusion approach implemented by means of a Kalman Filter (KF). The KF inputs were from traditional range-free [31] and range-based [32] localisation methods, according to [20]. The system accounted for a metre-level localisation accuracy (mean localisation error = 0.98 m) [29].

2.2 Phase II: Experimental Setting and Data Acquisition

The experimental protocol was realistically tested in the DomoCasa Lab (Peccioli, Italy), which reproduces a fully furnished apartment of 200 m^2 with a living room, a kitchen, a bathroom, a double bedroom and a single bedroom. The apartment was instrumented with user localisation network as described in [20,30]. The user location ZigBee anchors were distributed as described in [29].

As a proof of concept, in this study, the experimental session was conducted with three users: one male and two female, whose ages ranged from 27–30 (28.33±1.53).

The user was asked to wear the sensors, the mobile node for user position (as described in Fig. 1a), and to perform each specific activity in the specified room (Table 1) for a total of 3 mins. A PC is used to collect the data from the wearable sensors and to compute the user's position using information from the user localisation network.

2.3 Phase III: Feature Extraction

The aim of this phase was to prepare data for the analysis. The accelerometer data consisted of the following attributes: timestamp and acceleration value along the x, y and z directions. The physiological data consisted of the ECG value and timestamp, and the user position data report the user's location estimated with the relative timestamp.

In the first part of the analysis, the data were cut, pre-processed and conveniently filtered to reduce noise. As concern the accelerometer data, a fourth-order low-pass digital Butterworth filter was applied with a 5 Hz cut-off frequency. As for the ECG data, a fourth-order band-pass digital Butterworth filter was applied with 0.05 Hz and 60 Hz cut-off frequencies in order to reject the disturbance properly.

Then, the data were synchronised by means of the timestamp. These time-series were divided with time-window length of 7 s; furthermore, in order to handle transitions more accurately, an overlapping window-time of 50% was chosen.

The next step consisted of the feature extraction. As regard the accelerometer signals, only the time-domain features were considered and included in the analysis [4]. These features were: the mean value (M), the root mean square (RMS), the mean absolute deviation (MAD), the standard deviation (SD) and the variance (VAR). All these features were computed for each axis of the two sensors, for a total of 30 accelerometer features.

Starting from the ECG signal, the inter-beats (RR) interval was computed as the time interval between consecutive heart beats, and was practically measured in the electrocardiogram from the beginning of a QRS complex to the beginning of the next QRS complex. From the RR signal, three different features were extracted: the mean RR value (RRM), the standard deviation (RRSD) and the number of heartbeats per minute (BPM). The final feature of this dataset was represented by the user location, which indicates the micro-area where the activity was performed.

Within this phase, all these 34 features were computed for all the activities listed in the experimental protocol. Consequently, at the end of this phase, a dataset composed of 35 columns (the final column was the label of the activity) was obtained and manually labelled for each user. Table 2 reports all the features involved in the analysis.

Table 2. Features List

	Features		**Number**
Accelerometer	M	mean value	5 x 3 (axis) x 2 (sensors)= 30
	RMS	root mean square	
	MAD	mean absolute deviation	
	SD	standard deviation	
	VAR	variance	
Vital Sign	RRM	mean RR value	3
	RRSD	standard deviation	
	BPM	Heartbeat per minute	
User Location	User Location inside the house, indicated with microarea granularity.		1
		Total	34

2.4 Phase IV: Feature Classification

In this phase, the three users' datasets were merged into a unique dataset in order to reduce the users' physiological variability. Then, this dataset was randomly split into two parts (60% training set and 40% test set). The training set was used to build the models, whereas the test set was used for the evaluation phase, as will be described in Section 2.5.

Many supervised classification algorithms have already been employed in activity recognition tasks: Decision Tree (C4.5) [26], Fuzzy Logic [33], Support Vector Machine [34] and Hidden Markov Model [35], amongst others. Here, three different algorithms (DT, SVM and NN) were used to perform the recognition tasks. The models were built using (i) Classification Tree with 10 k-fold; (ii) Multiclass Support Vector Machine, adapted from [36], with a linear kernel; and (iii) a Feed-forward neural network. All these models were computed using the machine learning toolbox of Matlab 2012.

In order to evaluate whether user localisation could improve the accuracy, two different classification models were built on the training dataset: one including information on the user's position; the other, not.

2.4 Phase V: Evaluation

Within this phase, the two models were evaluated considering the test set (40% of the original dataset). The results were reported into a confusion matrix. Then, the precision, accuracy, recall, specificity and F-Measure metrics were used to estimate the effectiveness of the models [4] and to compare the performance of the three algorithms used.

Recall is defined as the ratio between the number of correctly classified instances of a class and the number of instances belonging to that class predicted as belonging to other classes. Overall recall is computed as the mean value.

Precision is defined as the ratio of correctly classified in each class to the total number of instances predicted as belonging to that class [33]. Overall precision value is computed as the mean value.

Specificity, also called the true negative rate, is the ratio between the total number of negative instances that were classified as negative, and the total number of negative instances classified in that class. The overall specificity value is computed as the mean value.

F-Measure combines the overall precision value and the overall recall value as follows:

$$\mathrm{F-Measure} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{(\mathrm{Precision}+\mathrm{Recall})} \quad (1)$$

Overall Accuracy is defined as the ratio between the number of correctly classified instances of a certain class and the total number of instances. It estimates the overall accuracy of the system.

These evaluation metrics were used to compare the activity recognition results gained by applying the DT, SVM and NN over the two models. The difference percentage (Eq. 2) was used to estimate the improvements quantitatively:

$$\mathrm{Difference\ Percentage} = \frac{P_N - P_Y}{P_N} \cdot 100 \quad (2)$$

Where P_N is the parameter of the model without the user's location and P_Y is the parameter of the other model.

3 Results and Discussion

In this section, the overall evaluation of the results obtained from phase V is reported and discussed. The analysis was conducted considering a total of 482 samples (60%), whereas a total of 193 samples (40%) were included in the evaluation phase.

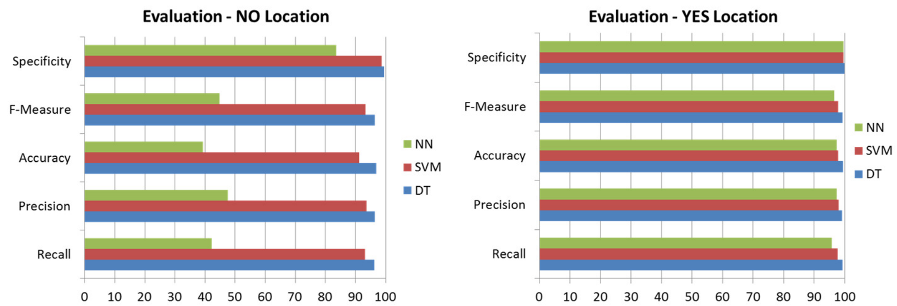

Figure 3. Performance of the three classification algorithms (NN, SVM, ST).

As shown in Fig. 3, the results obtained in this proof of concept suggest that the inclusion of information on user location could increase the performance of activity recognition (see Table 3). The NN approach presented the highest difference percentage between the two models (Recall +127%, Precision +104%, F-Measure +116%, Specificity +19%, Overall Accuracy +147%) from visual inspection of Fig. 3. The SVM model presented a higher increase in the performance rather than DT (Recall +5%, Precision +5%, F-Measure +5%, Specificity +1%, Overall Accuracy +7%). Finally, the DT comparison values were: Recall +3%, Precision +3%, F-Measure +3%, Specificity +0.4%, Overall Accuracy +2.67%.

Table 3. Overall evaluation metrics for the three classification algorithms (Overall Precision, Overall Recall, Overall Accuracy, F-Measure and Overall Specificity) for the two models (N = no user location, Y = user location). The values are expressed as percentages.

		Recall	**Precision**	**Accuracy**	**F-Measure**	**Specificity**
DT	**N**	96.34	96.43	96.89	96.38	99.57
	Y	99.26	99.22	99.48	99.24	99.93
SVM	**N**	93.22	93.62	91.19	93.42	98.68
	Y	97.74	98.03	97.93	97.88	99.70
NN	**N**	42.21	47.62	39.38	44.75	83.52
	Y	95.83	97.40	97.41	96.61	99.64

In particular, as regards the DT analysis, the overall accuracy was equal to 96.38% for the system without the information on the user's position; this result was comparable to other work that followed a similar approach [37]. On the other hand, the accuracy was equal to 99.24% for the model that included the user's location. Similar results were also obtained for the overall precision, which increased from 96.43.% of the first case to 99.22% of the second case. Comparable trends could be observed also for Recall and F-measure. Specificity was higher than 99% for both cases, meaning that both models were able to classify the negative instances as negative correctly.

For the SVM results, for the model without the user's location, we obtained comparable results to the state-of-the-art [4]. Considering the second model, the overall accuracy was increased from 91.19 % to 97.93 %, while the precision was increased from 93.62 % to 98.03%. Similar results were also obtained for recall and F-Measure. Both models showed similar specificity results; indeed it is the lowest difference percentage obtained in this analysis. NN recognition analysis had the worst recognition results without the user's location (Recall 42.21%, Precision 47.62%, Accuracy 39.38%, F-Measure 44.75%, Specificity 83.52%). However, these results are considerably improved in the model with the user's location. In fact, in this case, the overall accuracy was equal to 96.61%; similar improvements were also obtained for the other metrics. DT and SVM seem to be the best activity recognition approaches (Fig. 3).

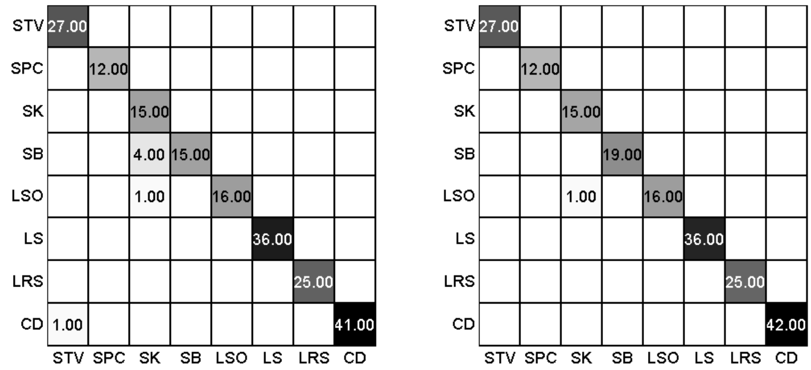

Figure 4. Phase V – DT Confusion Matrix of the test set. Left: results of the dataset without the user localisation. Right: confusion matrix obtained with the user localisation.

Table 4. Phase V: DT - Evaluation results for each activity. The values are expressed as percentages.

DT	No Location			Yes Location		
	Recall	**Precision**	**Specificity**	**Precision**	**Recall**	**Specificity**
STV	100	96	99	100	100	100
SPC	100	100	100	100	100	100
SK	100	75	97	100	94	99
SB	79	100	100	100	100	100
LSO	94	100	100	94	100	100
LS	100	100	100	100	100	100
LRS	100	100	100	100	100	100
CD	98	100	100	100	100	100

Concerning the analysis conducted considering the single activity with the DT algorithm, SB was the worst-recognised activity without user localisation (recall 79%), whereas SK was the activity with the lowest precision value (75%) (Table 4). In particular, analysing the two confusion matrices reported in Fig. 4, it is evident how "similar" activities like SB and SK could be easily confused because of the similar body posture and orientation, as shown in the confusion matrix. Consequently, information on the location can provide missing information for activity recognition. In fact, in the second model, the same activities were corrected classified.

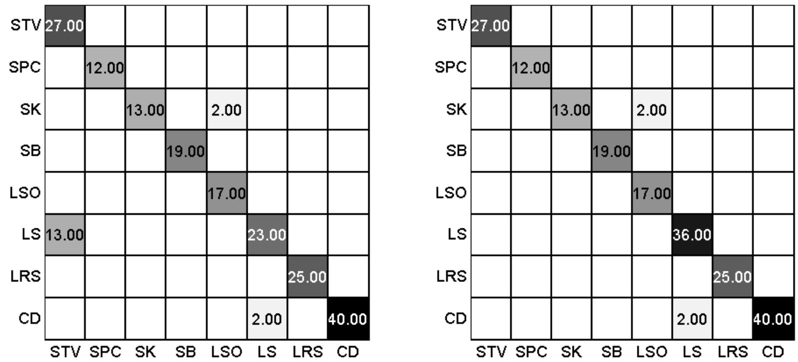

Figure 5. Phase V – SVM Confusion Matrix of the test set. Left: results of the dataset without the user localisation. Right: confusion matrix obtained with the user localisation.

Table 5. Phase V: SVM - Evaluation results for each activity. The values are expressed as percentages.

SVM		No Location			Yes Location	
	Recall	Precision	Specificity	Recall	Precision	Specificity
STV	100	68	92	100	100	100
SPC	100	100	100	100	100	100
SK	87	100	100	87	100	100
SB	100	100	100	100	100	100
LSO	100	89	99	100	89	99
LS	64	92	99	100	95	99
LRS	100	100	100	100	100	100
CD	95	100	100	95	100	100

For the SVM analysis (Fig. 5), LS were the activities with the lowest recall value (64%), while the activity with the lowest precision and specificity value was STV (68% and 92% respectively). The complete results for SVM models are reported in Table 5.

On the contrary, as regards the NN results, it is evident how STV, SK, SB and SPC and LRS and LS are mutually confused (confusion matrix: Fig. 6). Their recall values were 26%, 0%, 74%, 58%, 52% and 17% respectively. The LSO and LRS activities had the lowest specificity values (69% and 70% respectively). In the second model, the identification of STV, SK, SB, LS, LRS, and CD were improved significantly (Table 6).

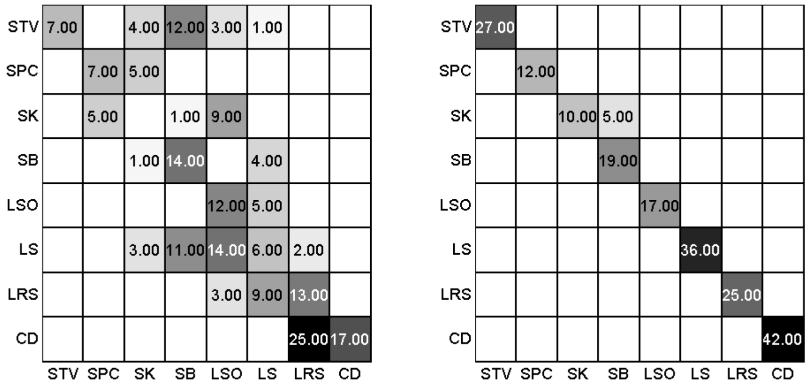

Figure 6. Phase V – NN Confusion Matrix of the test set. Left: results of the dataset without the user localisation. Right: confusion matrix obtained with the user localisation.

Table 6. Phase V: NN- Evaluation results for each activity. The values are expressed as percentages.

NN	No Location			Yes Location		
	Recall	Precision	Specificity	Recall	Precision	Specificity
STV	26	100	100	100	100	100
SPC	58	58	93	100	100	100
SK	0	0	85	67	100	100
SB	74	37	72	100	79	97
LSO	71	29	69	100	100	100
LS	17	24	79	100	100	100
LRS	52	33	70	100	100	100
CD	40	100	100	100	100	100

Analysing the state-of-the-art, it was evident how aggregate data (vital signs and accelerometer data) could improve activity recognition performance [14]. These preliminary results also suggest that the user's location can improve the accuracy and precision of an activity recognition model.

IoT and connected devices are becoming more common in our daily life. This means that there is much available information that could potentially be included in the analysis. In this proof of concept, user localisation was used as an example; other activity and service models can also be generated, including other types of information that comes from the pervasive use of connected devices and smartphones [38].

4 Conclusions

This work has presented a proof of concept where information on user indoor location has been used to reduce the number of wearable devices, therefore increasing the overall accuracy of the system. Indeed, the overall accuracy values were satisfactorily increased (+2.67% DT, +7.39% SVM, +147.37% NN) in the model with information about the user's location.

The presented system was tested in a realistic environment with three users in order to assess the feasibility of the concept design. These results encouraged the use of this approach in activity recognition applications. Thinking to apply and to exploit this method to real-time cases in a cloud computing design, other considerations concerning the processing efficiency, should be made. As stated by Yuan et al. [39], DT is the optimal choice to be performed on the cloud in terms of efficiency. However, they found an accuracy of about 95% for DT (and SVM). The method presented in this proof of concept increases the overall accuracy without also increasing the number of sensors placed on the user's body

Future tests will be performed in order to increase the number of participants in the experimental settings. Future improvement of the systems should also include "movement" activities (i.e. walking, descending/ascending stairs) in order to evaluate whether the user's location can increase the accuracy of these kinds of activities.

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