Smart Cup to Monitor Stroke Patients Activities during Everyday Life

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***Abstract*—This paper presents a new platform to monitor stroke patients activities during their everyday life at home. This platform is intended to be a part of a smart objects ecosystem for home monitoring using common objects embedding sensors. The monitoring is performed with a self-contained smart cup that can be used to drink at different times of the day. The smart cup embeds various sensors in order to detect its movements and the liquid level. Activity analysis is performed on the collected data in order to provide information to the therapists on the patient's sedentariness and independence on the daily life tasks (sitting, walking, drinking and going up and down the stairs). This paper presents the design concept of the smart cup along with the implementation and mainly focuses on the activity analysis process. We used a linear classifier: the Support Vector Machine (SVM) classifier. Indeed, the classification of stroke patient's activities is a binary classification. Moreover, as we decided to use DCT features, SVM is the classifier that gives better classification performances. The results show a recognition precision above 92% on all activities with the smart cup. A comparative study has been carried out in order to assess the performances of the linear SVM classifier and a non-linear Multi-Layered Perceptron (MLP) classifier. The result of this study shows that the linear SVM classifier offers better performances on classifying everyday life activities with a smart cup.**

***Index Terms*—Stroke, Monitoring, Internet of Things, Home, Activity Recognition**

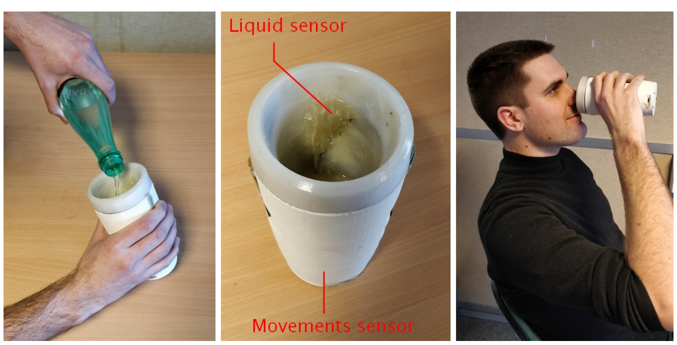

Fig. 1: An overview of the SyMPATHy cup prototype.

I. Introduction

Rehabilitation is a common process after a stroke that can affect cognitive or motor functions. Motor recovery is a long and crucial process for the independence of the patient in the daily life and stroke monitoring and rehabilitation are very expensive since they require costly infrastructures and involve medical staff for long periods [1]. Furthermore, once home, no medical monitoring is performed on the motor activities of the patients. Monitoring activities such as walking, sitting, standing or drinking would allow the therapists to assess the patient's sedentariness and independence in the everyday life. This assessment would allow therapists to suggest a readmission to the hospital to the patient in order to enhance its independence through specific exercises during rehabilitation sessions.

Different platforms have been developed in order to assess the motor activities of human beings. Some approaches are based on vision systems that can be fixed in the environment [2]. However, these solutions are inadequate and present several constraints due to the hardware and software complexity of the platforms. For example, when several vision sensors are involved to cover a large space, calculation can be expansive. The robustness of tracking is also limited when users are partially or totally outside the vision space. Other approaches for monitoring human activities are based on devices carried by humans (e.g. smartphones or smartwatches) [3]. Many studies investigated the activity recognition with sensors by fixing the devices on some locations on the body (e.g. smartphone in pocket) [4], [5]. However, wearing sensors can be intrusive for the users.

The recent development of Internet of Things (IoT) and particularly wearables allows to collect more consistent data at a lower cost and opens the door for many perspectives in the field of human activity recognition. These new platforms are cheap, lightweight and based on devices equipped with different types of embedded sensors (e.g. inertial measurement units, proximity sensor, force sensor, temperature sensor, health rate sensor) and displays wore by users. These platforms provide a powerful tool for monitoring Activities of the Daily Living (ADL) such as walking, sitting, standing or drinking, which seems to be good outcome predictors for stroke recovery [6]. Many researches investigated the recognition of human activity using smart objects and wearables [7], [8], [9], [10], [11], [12]. However, some researches on physical activity recognition require a usage in specific configurations: either they asked participants to perform specific tasks (e.g. standing, sitting, walking upstairs) [13] or they annotated the placement of the device at the beginning of the activity (e.g. in pocket, purse, hand) [14].

Based on the data collected by these systems, different methods exist to detect and classify activities and can be divided in two categories: linear and non-linear algorithms. Linear algorithms allow to separate classes with a linear function while non-linear algorithms use a non-linear mathematical function to separate classes. For example, Decision Trees (DT) and SVM are linear algorithms and have been used to recognize users activities such walking, sitting, running or vacuuming with a good precision [15], [16], [17], [5]. These algorithms tend to be easy to use and have a fast learning phase. On the other hand, non-linear algorithms such as Random Forest [14] or k Nearest Neighbors (k-NN) [18] exist to recognize activities with a good precision. For example, a combination of Neural Network (NN) and Hidden Markov Model (HMM) allowed to recognize when the user is sitting, walking or sleeping with a precision above 87% [13]. Moreover, Gao et al proposed a comparative study of five popular classifiers (SVM, Naive Bayes, DT, NN and k-NN) and showed that DT classifier is suitable for multi-sensor wearable platforms [4]. In addition, two main methods exists to determine features used with these algorithms: (1) using the discrete cosine transform (DCT) [19] by making a transformation in the frequency domain or simply by using the technique of reduction in the characteristics of the coefficients of the magnitude of the spectrum [20], or (2) using a temporal approach with the average cycle method by segmenting the signal. Using one of these methods depends on the type of signal retrieved during data collection.

Although wearables provide reliable tools for monitoring stroke patient's activities outside the home during the day, they are not always used at home. As our society tends to inter-connect daily objects and make them smart [21], [22], using smart devices (cups, forks, etc.) based on common daily objects embedding sensors seems to be a complementary solution to enhance the monitor stroke patients without modifying their home habits. Indeed, an ecosystem of smart objects embedding sensors could take over from wearables when the patient comes home and merging data from all the objects in the ecosystem should enhance activity recognition performances.

Post-stroke patients can often go home without having fully recover the usage of their disabled limbs and perform basic tasks such as walking, sitting or drinking can be a constant challenge during the everyday life. These basic tasks require the coordination of the upper or lower limbs that can be still uncertain at the early stages of home recovery. Monitoring these ADLs without disturbing the patient's habits seems relevant for assessing remotely its recovery and helping the therapists to adapt the rehabilitation exercises performed during rehabilitation sessions at the hospital in order to suit the patient's progress and provide more suitable exercises. This paper presents a smart cup, called SyMPATHy (see Figure 1), based on a common daily object used during the day for drinking (water, coffee, etc.). SyMPATHy embeds various sensors providing information on the way the patient fills, holds and manipulates the cup. The platform is therefore able to monitor five everyday life activities (sitting, standing, walking, going up and down stairs and drinking) allowing the therapists to assess the overall body activity of the patients and detect sedentariness or dependence on some daily basic tasks. In the future, SyMPATHy is intended for being a part of a smart objects ecosystem designed for monitoring everyday life activities at home with common objects allocated for specific tasks (a cup for drinking, a broom to clean the house, etc.).

This paper addresses the design concept of SyMPATHy in the section II including the monitored data. Then, the implementation of the prototype is presented in the Section III. Afterwards, the section IV is devoted to the activity analysis method using a SVM classifier and a comparative study with a Multi-Layer Perceptron (MLP). Finally, conclusion and prospects for the SyMPATHy platform are presented.

II. Design Concept

The smart cup have been developed in order to monitor motor activities of stroke patients at home without disturbing the patient's life. SyMPATHy embeds different sensors allowing the therapists to assess the patient's physical state, sedentariness and dependence on daily basic tasks with activity analysis.

The design process of SyMPATHy includes two main steps: 1) identify the best object for activity monitoring at home (Section II-A) and 2) identify consequently the information to be monitored (Section II-B).

A. Identification of the best object

Two qualified health professionals working at a stroke rehabilitation center were interviewed in order to identify the best object for sensor integration allowing to monitor motor activities of stroke patients. The interviews highlighted that instrumenting objects involved in ADLs would allow an easier acceptance of monitoring systems. Moreover, Timmermans et al. showed that positioning and manipulating tasks require a good coordination of upper limbs' movements and are generally based on an action-perception loop exploiting several sensory channels (vision, tactile, proprioception, audio) [23]. A typical activity involving positioning and manipulating tasks is drinking. Indeed, the patient has to grasp the bottle and the cup, raise the bottle above the cup and control the amount of liquid poured into the cup. This activity involves motor actions with different parts of upper limbs (hand, arm, etc.). Moreover, it simultaneously involves vision, tactile, proprioception and audio sensory feedback. In addition, health care professionals mentioned that monitoring basic tasks with the cup such as walking or standing is possible as patients can drink while standing or fill the cup in the kitchen and move to the living room while holding the cup.

According to the previous research and interviews' feedback, we decided to develop a smart cup able to monitor when the patient drinks as well as the overall body activities. Indeed, drinking is a crucial task for health and independence. Moreover, overall body activities including basic activities such as walking, sitting, standing or going up and down the stairs are also crucial for independence in the house and are often performed while holding a cup.

B. Monitored information

In order to assess the patient's recovery progress and independence in the daily basic tasks, the information to be monitored has been divided in two categories: (1) the overall body activity and (2) the drinking activity. The overall body activity is assessed by monitoring basic tasks (sitting, standing, walking, etc.) through activity analysis while the monitoring of drinking is assessed by merging data from the activity analysis and the liquid level of the cup.

1) The overall body activity: The analysis of the overall body activity of the patient is based on the movements data collected by SyMPATHy. This data is used to perform activity recognition and monitoring allowing therapists to access to the sequence of activities made by the patient as well as the distribution of the patient's activities over the day. The therapists can thus assess the patient's progress as well as the evolution of the patient's dependence and sedentariness.

2) The drinking activity: The monitoring of the drinking activity is based on the movements data and the liquid level information collected by SyMPATHy. Monitoring the liquid level i.e the quantity of liquid poured into the cup would allow the therapist to evaluate the accuracy and coordination of movements during the filling. In fact, pouring water into a cup is a real challenge for motor deficient stroke patients. Moreover, tracking the movements of the cup during manipulation would allow the therapist to understand the way the patient holds the cup (vertically or not) and potentially detect motor disorders. In fact, the motor, sensory or cognitive disabilities may lead to wrong postures where the cup is not held vertically. Activity analysis also allows to detect when the user drinks based on the movements of the cup. Finally, merging data indicating the liquid level as well as the movements of the cup allows to improve the drinking activity recognition by avoiding false positive such as when liquid is spilled off the cup by the patient.

III. Implementation of the prototype

SyMPATHy prototype embeds a series of sensors described below that collects the data required to perform the different data processing. All the data collected by SyMPATHy is sent to a remote computer via wireless communication.

A. Liquid level detection

Due to the constraints of industrial liquid level sensors (low-reactivity, size, etc.), SyMPATHy embeds its own custom sensor based on the measurement of the liquid conductivity. Five conductive electrodes were placed vertically inside the cup. The electrodes are spaced one centimeter from each other. Each discrete level corresponds to a volume of 100 ml. Electrodes act as switches and liquid allows to close the circuit. When liquid is poured into the cup, one or several voltage divider bridges are activated which modify the resistances measured by Analog-Digital-Converters.

B. Movements detection

SyMPATHy embeds an Inertial Measurement Unit (IMU) that embeds an accelerometer, a gyroscope and a magnetometer. Each of these sensors returns three values on the three axis x, y, z. Moreover, data are sampled at 30Hz.

The data collected by the IMU sensor are used by the machine learning algorithm to analyze and classify the activities of the patient (See section IV). The data processing is performed off-line on the computer. Indeed, this design choice seemed the best solution in terms of power consumption, power computation and roll-out.

IV. Activity Analysis using SVM

This section presents the methodology followed to recognize patient's activities using a SVM classifier. We decided to use SVM algorithm as it reaches good classification precision compared to other algorithms (kNN, Bayes; Logistic classifier, C4.5, Decision Trees, VFDT, RNN ...) [24], [25], [26]. This study is based on healthy subjects in order to demonstrate the feasibility of activities recognition such as sitting, standing, walking or drinking with a smart cup.

A. Data collection

15 participants were involved for the data collection. The participants were 2 females and 13 males aged between 22 and 29 (M = 25.6, SD = 1.9). In order to simulate more realistic tasks during the everyday life, participants were asked to perform the tasks listed below during 10 minutes continuously. This behavior was inspired by post-stroke patient's activities at home during the day. The simulated activities appear to be relevant and easily controllable after a discussion with health care professionals.

The monitored activities are the following:

- Sitting (See Figure 2.a)
- Standing (See Figure 2.b)
- Drinking (See Figure 2.c)
- Going up and down the stairs (See Figure 2.d)
- Walking (See Figure 2.e)

Fig. 2: Photos of the tasks performed by the participants: a) sitting, b) standing, c) drinking, d) going up and down stairs and e) walking.

The data was recorded from the IMU embedded in the smart cup at a sampling frequency of 30Hz via wifi under controlled conditions in a laboratory corridor.

After collecting data with the participants, the following process was followed in order to analyze the different activities:

1. Extraction of a useful signal
2. Calculation of signal's representative key points
3. Concatenation of the features
4. Creation of the database for future learning

B. Extraction of a useful signal

The figure 3 shows an illustration of the accelerometer signals recorded during the walking task. The abscissa axis represents the time (in seconds) and the ordinate axis the acceleration (in multiples of g, the gravity).

A segmentation of the signals was performed to allow stable, similar and therefore non-noisy periodic signal sequences as shown in the figure 4.

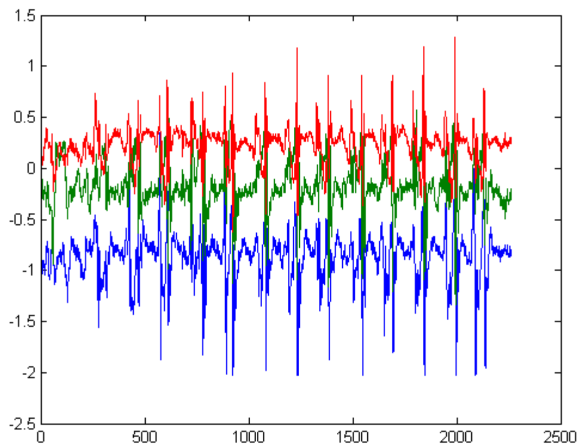

Fig. 3: Signals representation of the "walk" activity.

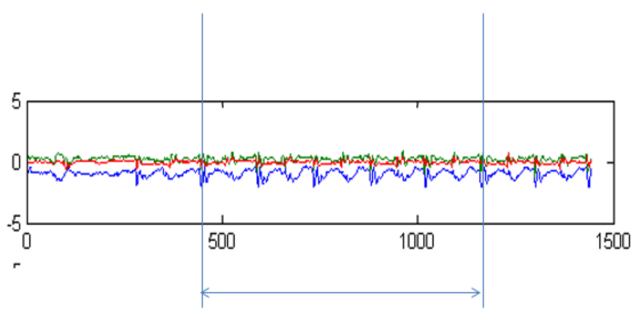

Fig. 4: Segmentation, cleaning and extraction of a useful signal.

C. *Calculation of signal's representative key points*

Before applying any learning algorithm, data has to be compressed. The data compression consists in finding representatives key points of the studied signal. These representatives key points are called features and act as a fingerprint to characterize the signal.
We used the discrete cosine transform DCT as a feature with the SVM classifier and more precisely the DCT-II [19]. Indeed, the DCT is a good signal decorrelator, but also has the peculiarity of regrouping of the energy, in the low frequency coefficients thanks to its approximation of the Karhunen-Love transform of main component analysis.

The DCT of a sample X(n), n=0, 1, (N-1) is given by:

$$X_0 = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n) \quad (1)$$

$$X_k = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} x(n) \cos \frac{(2n+1)\pi k}{2N}, k = 1..(N-1) \quad (2)$$

As X_k is the K^{th} DCT coefficient, all the N coefficients of the DCT can be calculated using a 2N-length Fast Fourier Transform (FFT). Moreover, when the sampling frequency is normalized to 1, X_k is a bandpass filter having a center frequency at $\frac{2k+1}{2N}$. The amplitude of the output X_k is therefore greater when k is small, i.e. DCT can be concentrated in the low DCT indexes if the remaining coefficients can be zeroed without significant impact on signal energy.

However, as the signals recorded with the IMU sensors are not homogeneous, these signals have to be cut in regular and equal portions (Figure 5). Indeed, analyzing the whole signal can cause an over-fitting i.e. the learning model will learn by heart the data and the generalization will be inaccurate. The aim is to choose wisely the size of the cutting window in order to reach the best precision and define if overlapping brings more precision in the calculations.

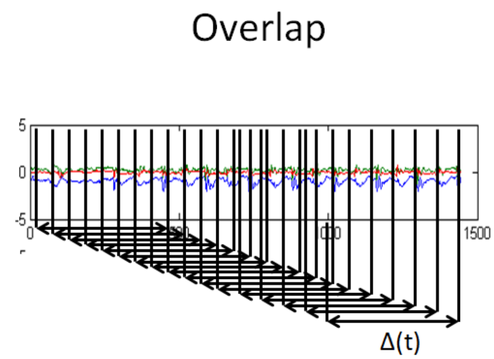

Fig. 5: Cutting of the signal.

1) Size of the cutting window & overlapping: Three cutting window sizes, represented with Δt, were investigated with and without overlap: 128 samples (1.06 seconds), 256 samples (2.13 seconds) and 512 samples (4.26 seconds). It should be noted that going beyond 512 points per window could compromise the real-time aspect of the response.

The results show that the best performances are obtained with a cutting window size of 512 with overlap for each sensor (accelerometer, gyroscope and magnetometer) on each activity. The table I presents the performances of activity recognition for the accelerometer signal. Similar results are obtained with the gyroscope and the magnetometer. The average performances for the accelerometer, gyroscope and magnetometer are respectively 93.37%, 85.49% and 82.86%. These parameters will be used to calculate the signal features of the three sensors.

Δt	128		256		512	
	Off	**On**	**Off**	**On**	**Off**	**On**
Walking	60.10	69.30	78.04	88.02	89.01	**93.33**
Standing	60.21	66.66	70.10	78.21	90.21	**92.81**
Sitting	65.54	70.50	78.10	80.14	90.21	**94.03**
Up/Down	65.20	70.30	76.20	80.54	88.20	**91.33**
Drinking	70.20	75.30	80.01	80.20	92.20	**95.36**

TABLE I: Classification performances in % of the activities with the three size of cutting window with and without overlap according to the accelerometer signal.

2) Feature size: After determining the size of each cutting window, calculations have been carried out to determine the size of the feature for each sensor (Figure 6) which gives better classification performances.

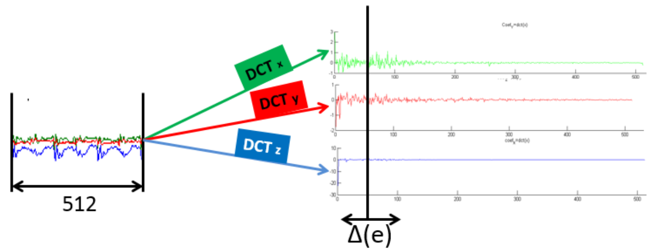

Fig. 6: Calculating features for each axis for each sensor.

Seven Δ(e) sizes were investigated between 2 and 64 including 2, 4, 8, 16, 32, 48 and 64. Results show that a feature of size 32 gives better classification performance for the accelerometer signal and the magnetometer. On the other hand, a feature of size 48 gives better classification performance for the gyroscope. The figure 7 presents the results for the accelerometer.

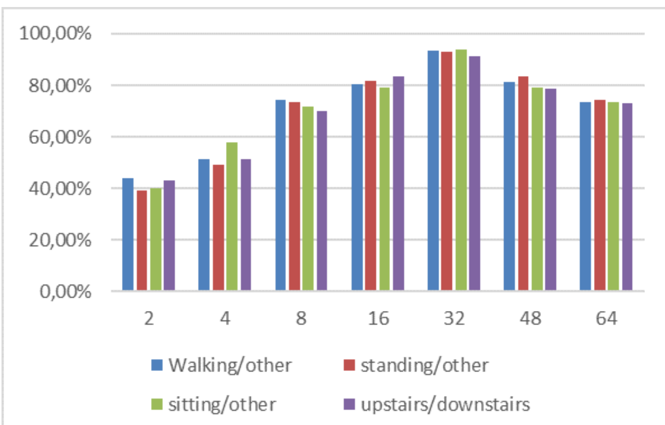

Fig. 7: Classification performances according to the value of Δ(e) according to the accelerometer signal.

D. *Concatenation of the features*

Each sensor of the IMU (accelerometer, gyroscope and magnetometer) is composed of three axis. It is required to see whether using only one axis is enough to reach a good precision or merge axis allows to have a better precision. The attention was focused on the features constructed from the three axes, X, Y and Z, but also for the X axis and for the Y axis. The classification performances are obtained with a 512 cutting window with an overlap of 256 and a feature size of 144 (48 * 3) for the gyroscope, 96 (32 * 3) for the accelerometer and the magnetometer.

The concatenation of the three axes for each sensor (accelerometer, gyroscope and magnetometer) allows to achieve better classification performances. The results are summarized in the tables II for the accelerometer, III for the gyroscope and IV for the magnetometer.

Finally, we investigated the concatenation of the three sensors features. First, we tried all the concatenation combination

Δt / Activity	X	X, Y	X, Y, Z
Walking	89.89	92.48	**93.33**
Standing	91.03	91.78	**92.81**
Sitting	92.66	93.07	**94.03**
Up/Down	88.39	90.89	**91.33**
Drinking	89.89	92.48	**95.36**

TABLE II: Performances in % according to the choice of the axes for the accelerometer.

Δt / Activity	X	X, Y	X, Y, Z
Walking	83.66	84.87	**85.03**
Standing	80.99	81.81	**82.81**
Sitting	84.99	85.33	**86.03**
Up/Down	79.36	81.84	**82.33**
Drinking	81.29	88.20	**91.28**

TABLE III: Performances in % according to the choice of the axes for the gyroscope.

Δt / Activity	X	X, Y	X, Y, Z
Walking	78.98	79.45	**80.16**
Standing	79.92	80.59	**81.01**
Sitting	83.95	85.67	**86.23**
Up/Down	87.07	87.98	**88.01**
Drinking	62.36	71.36	**78.89**

TABLE IV: Performances in % according to the choice of the axes for the magnetometer.

(accelerometer + gyroscope, accelerometer + magnetometer and gyroscope + magnetometer). Then, we concatenated the three sensors features. It appears that the concatenation of the three sensors features gives the best results reaching a mean precision of 94.33% on all activities with the SVM classification. Moreover, the concatenation of the sensor signals for "drinking" activity gives the best results compared with the other activities with a precision of 96.98% (See Table V).

	A	A+G	A+M	G+M	A+G+M
Average	92.87	93.45	89.32	78.20	**94.33**
Drinking	93.98	94.09	93.02	69.21	**96.98**

TABLE V: Results of the concatenation of the sensors features in % (A: accelerometer, G: gyroscope, M: magnetometer).

E. *Creation of the database for learning*

The determined DCTs of each axis (X, Y, Z) of each sensor have been concatenated to form features stored in a database, which have been used for the classification step. During the classification process, the data-set has been subdivided in a training set and a test set. The learning phase was performed by the 10-fold cross validation method.

F. *Results*

Two confusion matrices have been computed (See Table VI and VII) in order to assess the reliability of the SVM model. It can be mentioned that the SVM model is pretty good in classifying ”Standing, Sitting, Walking and Going Up and Down the stairs”. For example, 218 cases were correctly classified as ”Standing” while only 18 were classified as another activity. Out of 386 where the participant drank, the model predicted that he was drinking. The model predicted 14 times that the participant was not drinking while he actually was drinking. There is only 31 cases where the model predicted that the participant was not drinking while he was actually drinking.

Real \ Estimated	**Standing**	**Sitting**	**Walking**	**Up/Down**
Standing	**218**	10	3	5
Sitting	7	**206**	5	1
Walking	3	1	**200**	11
Up/Down	2	1	1	**298**

TABLE VI: Confusion matrix for human activity recognition with the SVM model.

Real \ Estimated	**Drinking**	**Not**
Drinking	**386**	14
Not	31	**369**

TABLE VII: Confusion matrix for the ”drinking” activity recognition with the SVM model.

After extracting non-noisy periodic signal by segmentation, features were calculated by using the DCT algorithm. Features are representatives specific patterns of the signal. They allow to easily identify the signal like a fingerprint. Then, three cutting window sizes were investigated (128, 256 and 512) as well as the use of overlapping with the SVM classification algorithm. It results that the performances with a cutting window size of 512 with overlap are far much better than any other configuration and this for each sensor (accelerometer, gyroscope and magnetometer). Afterwards, the features size have been determined in order to get best performances. It results that the feature size is set to 32 for the accelerometer and magnetometer and 48 for the gyroscope. Then, it has been demonstrate that the concatenation of the three descriptors (X, Y and Z) for each sensors shows better results for activity recognition. Finally, fusion was performed to enhance the precision of activity recognition. The fusion of the three sensors gives the best results (94.33% on activity recognition and 96.98% for the ”drinking” activity).

V. Comparative study with a multi-layered perceptron

In order to compare the efficiency of the linear SVM algorithm, we implemented a non-linear classification method using a neural network. We decided to used a multi-layer perceptron (MLP) which is a ’reference’ non-linear algorithm. The previous results give best performances with features’ dimensions equal to 96 for the accelerometer and magnetometer and 144 for the gyroscope. These features’ dimensions are very high for estimating the parameters of an MLP. In order to remedy this problem, the size of the data has been reduced using a Principal Component Analysis (PCA).

A. Reduction of the data size

We managed to reduce the size of the data with PCA by varying it from 144 to 20 to 5 to 2 for the gyroscope and 96 to 20 to 5 to 2 for the accelerometer and magnetometer.

B. Determination of the hidden layer’s size

The number of neurons on the hidden layer is determined by the following method: (1) extraction of a set of learning and testing, using 10-fold cross validation, (2) extraction of the learning algorithm of the MLP for a number of neurons of the different hidden layer (m $\in \{1, 3, 5, 7, 9, ..., 49\}$) and (3) calculation of the performances in generalization.

The results show that 3 neurons on the hidden layer and 5 dimensions of the features allows the best recognition precision with the accelerometer reaching 85.66% (See Table VIII). However, only 1 neuron on the hidden layer and 5 dimensions allow the optimal classification performance for the gyroscope (78.32%) and for the magnetometer (72.29%).

# neurons \ Dimension	**2**	**5**	**20**
1	73.56	79.02	74.33
3	73.89	**85.66**	68.33
5	70.36	71.99	67.95
7	69.89	69.15	66.33
9	65.65	62.33	60.33
11	60.28	55.39	50.39
49	49.39	45.33	42.39

TABLE VIII: Performances in % according to the number of neurons in the hidden layer according to the size of the feature for the accelerometer.

C. Results

Two confusion matrices have been computed (See Table IX and X) in order to assess the reliability of the MLP model. It appears that the model is pretty accurate and for example recognize correctly the ”Up/Down” activity 215 times while the model is wrong only 87 times. Out of 387 where the participant drank, the model predicted that he was drinking. The model predicted 13 times that the participant was not drinking while he actually was drinking. There is only 18 cases where the model predicted that the participant was not drinking while he was actually drinking.

Real \ Estimated	**Standing**	**Sitting**	**Walking**	**Up/Down**
Standing	**162**	23	6	45
Sitting	12	**144**	10	53
Walking	23	21	**118**	53
Up/Down	2	3	82	**215**

TABLE IX: Confusion matrix for human activity recognition with the MLP model.

Real \ Estimated	**Drinking**	**Not**
Drinking	**387**	13
Not	18	**382**

TABLE X: Confusion matrix for the ”drinking” activity recognition with the SVM model.

This comparative study aimed to compare the SVM linear classifier algorithm performances with the MLP non-linear classifier performances. This study allowed to choose wisely the number of neurons in the hidden layer for each sensor as well as the dimension of the data to reach the best performances. The use of PCA to reduce the size of the features gives performances of 85.66% for the accelerometers signals, 78.32% for the gyroscope and 72.29% for the magnetometer which is much less efficient than SVM. This leads to the conclusion that SVM is better than MLP in classifying activities.

VI. Conclusion and perspectives

The paper presents a working prototype of SyMPATHy, a self-contained smart cup, designed for monitoring stroke patient's activities of the daily living at home. Activity recognition has been performed with a SVM classifier in order to detect when the user is sitting, standing, walking, going up and down stairs and drinking. The precision of the activity recognition for these tasks is above 92%. Furthermore, a comparative study has been carried out between SVM and MLP and results show that SVM is better than MLP in this context.

Future works will address several issues. First, based on the SyMPATHy cup, a study is planned to investigate the usability and acceptability of the smart cup with stroke patients. Then, it would be interesting to complete the activity recognition process to be able to quantify the quality of the drinking task i.e. tell to the therapists how well the patients realize the drinking task correctly. Furthermore, information retrieval related to movements such as linear acceleration or translation amplitude could provide complementary characteristic information of the movement.

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