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Basic Daily Activity Recognition with a Data Glove

Julien Maitre[a], Clément Rendu[a], Kévin Bouchard[a], Bruno Bouchard[a], Sébastien Gaboury[a]

[a] *Université du Québec à Chicoutimi, 555 boulevard de l'Université, Chicoutimi G7H2B1, Canada*

Abstract

Many people in the world are affected by the Alzheimer disease leading to the dysfunctionality of the hand. In one side, this symptom is not the most important of this disease and not much attention is given to this one. In the other side, the literrature provides two main solutions such as computer vision and data glove allowing to recognize hand gestures for virtual reality or robotic applications. From this finding and need, we decided to developed our own data glove prototype allowing to monitor the evolution of the dysfunctionality of the hand by recognizing objects in basic daily activities. Our approach is simple, cheap (~220$) and efficient (~100% of correct predictions) considering that we are abstracting all the theory about the gesture recognition. Also, we can access directly and easily to the raw data. Finally, the proposed prototype is described in a way that researchers can reproduce it.

Keywords: Data glove; Object recognition; Basic daily activities; Signal processing; Machine learning ;

1. Introduction

These last few decades, the Alzheimer disease is becoming one of the most common causes of dementia [26]. More specifically, this disease acts directly on the brain creating at the same time some dysfunction of the human body. Different symptoms associated with this condition exist such as the difficulty in performing simple tasks, language problems, loss of orientation and, probably the best known, the loss of memory [2]. Thus, with the aging of the population that we can currently observe in all the modern societies, this disease is now considered as a priority in biomedical research. As a result, many researchers are working to discover new aspects of the disease to better understand how it affects the brain [29]. Among the proposed solutions, much attention has been given in neuro-rehabilitation therapy to restore the functioning of the hand [23]. Indeed, the hand permits to grasp some objects,

* Corresponding author. Tel.: +1-418-376-0916
E-mail address: julien.maitre1@uqac.ca

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to interact and produce changes with their environment, and consequently, it represents an essential part of people's everyday life.

At the same time, the significant advance of new technologies over the past 15 years made obsolete conventional input devices for customized human-machine interaction such as keyboards and computer mouse, which have become less-efficient solutions. This trend is a direct consequence of the availability of new technologies that can be integrated. Indeed, micro technologies allow the integration of sensors in the textiles [18]. Thus, those textiles can be used as sensors, actuators or networks [18, 4]. Also, the means of communication such as radio, GPS, GSM, Bluetooth, Wi-Fi, screen and keyboard are devices that can be integrated into textiles giving to these clothes a form of intelligence. These modern textiles fit perfectly into the daily lives of patients. They do not interfere with movements and are in phase with the modes of interpersonal communication. They are also intuitive and natural. Thereby, modern textiles fit well in the daily lives of users for monitoring their health. It is finally a patient's need, for more comfort in healing, less pain, to live in their own family environment.

In recent years and with the new needs of virtual reality and robotics applications, many researchers have worked on the recognition of gestures based on data gloves [17, 15]. The data glove can provide a natural and effective human-computer interaction tool for the user. The advantages of this technology compared to computer vision methods are: the quantity of elements received by the sensors is small and the speed of identification is significant. Also, the three-dimensional position of the hand and information on the movement of the fingers can be obtained directly, and many types of actions can be analyzed continuously. Unlike static gesture recognition, a real-time prediction system can judge the intent and allows knowing the exact final gesture. Some achievements have been made to determine the movements of human fingers and the feasibility of using the data glove system as a goniometric device (device which computes angles) has been demonstrated [10]. In addition, data gloves are widely used in many studies, including applications in virtual reality [15], robotics [13], and many telecommunication and biomechanical studies [4]. Consequently, their commercialization is not surprising, and all the data gloves that can be found on the market come with an SDK and a hand simulator application software. Prices start at $ 600.00 US for some basic models and can reach thousands of dollars for the most sophisticated ones. The cost aside, another drawback is that most commercial gloves are only compatible with the Windows operating system. In addition, the SDK is not always suitable for many other sensors. An alternative option is to develop a handcraft version of the data gloves. This effort is facilitated by the access of inexpensive microcontrollers, such as the Arduino. Finally, in order to discern a user-made movement, the gesture recognition mainly uses artificial neural networks, the hidden Markov model and the support vector machine [14]. However, the sensor readings of the data glove must be first processed, analyzed and then adapted to one of the known types of grasping.

Thus, in this work, we propose a specific prototype of data glove for basic daily activity recognition such as *hold a spoon*. In other words, the prototype allows us to recognize objects used in the basic daily activities. Unlike the data gloves and studies exploiting this one, we do not focus on the gesture recognition and application related to virtual reality, robotics, or sign language. Indeed, the data glove corresponds to a solution for monitoring the evolution of the Alzheimer disease through the object recognition. Also, we show in this study that the simplicity of the proposed approach works well and can be used to monitor the dysfunctionality evolution of the hand in a case of Alzheimer disease by taken into account the number of basic actions that cannot be recognized. Finally, unlike the commercial data gloves, the proposed prototype provides an acess to the raw data and can be reproduced by any researchers for few dollars.

2. Related works

One of the problems that is regularly encountered in the literature is the interaction between the hands and the shape of objects, which implicitly limits the behavior of the hand. Several taxonomies on the way in which the fingers are in contact with the object have been developed allowing to classify the different types of hand grasps. In [12], Edwards and McCoy-Powlen present various observations made on the hand such as the functional aspects of prehensions, or anatomical characteristics. Also, it exists several works summarizing all possible ways of grasping with one hand [21, 19]. Liu, J *et al.* [19] provide one of the most comprehensive datasets of achievable interactions with a human hand. For example, to grind is an hand-object interaction defined by : Apply greater compressive force than the

Fig. 1. Arrangement of the sensors on the hand.

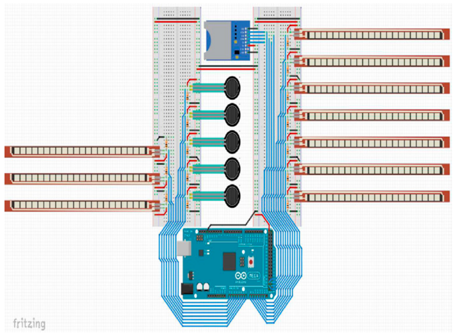

Fig. 2. Electric Schema of the data glove.

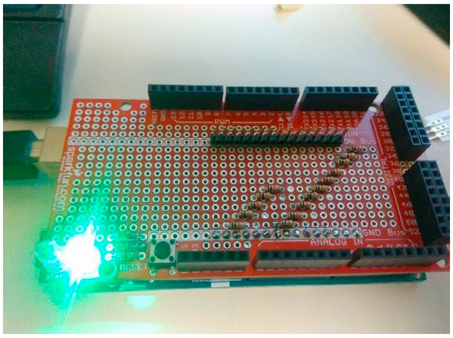

Fig. 3. Printed circuit board.

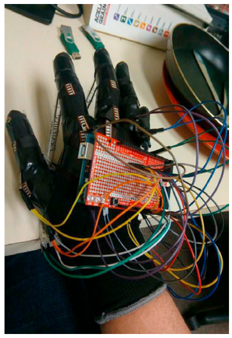

Fig. 4. Data glove prototype.

compressive force to hold the object. Thus, according to Murthy and Jadon [24], there are basically two approaches allowing to capture hand gestures: computer vision techniques and data gloves.

From the computer vision perspective, in recent years, many studies have been conducted using digital cameras [27] or depth sensors that provide three-dimensional data of the scene, such as the Leap Motion controller [22] and Microsoft Kinect hardware [8]. Stansfield [28] proposed a knowledge-based approach for grasping an unknown object with a camera. Researchers agree that some problems remain in computer vision, especially for gestural prediction. Indeed, it is still imprecise on certain points (real-time, light exposure, evaluation of distances, ...)[3]. In addition, significant computational costs and time for algorithms slow down the progress in the domain. Barros *et al.* [3] describe these phenomena in their work. They specify, for example, that for an arithmetic method of classification such as an artificial neural network, the data must be normalized first which represents a very time-consuming step.

Then, we can focus on studies done with the data gloves. Over the past decade, several authors have proposed different methods based on inertial, optoelectronic or electromagnetic sensors to measure the parameters of interpersonal physical interaction [1]. Some researchers focused on the static recognition of gestures, such as Preetham *et al.* in [25], while some are more attracted to the shape analysis systems in real-time, as described in the paper by Liu and Xiao [20]. Dipietro *et al.* [11] listed the different sensors used by the data gloves and in which case they were used. They point out that the main areas of exploitation in the past have been industry, robotics, art and the comprehension of sign language, whereas today it is mostly found in medicine and management of central units.

The major inconvenient of the data glove compared to the computer vision is that the study is done only on a well-defined local area that represents the hand. Nevertheless, the data glove compensates this problem by providing much more precise elements than computer estimation. A data glove allows obtaining information like the angle of each articulation movement and the state of the finger gestures in real time [25]. That is why, in this study, we use a data glove to detect the different object held by a human hand.

3. Data glove prototype

The design of the data glove is straighforward. Indeed, the first thing to do is to determine the locations and the type of sensors composing the data glove. The sensors allow acquiring information to recognize objects. To do so, it is necessary to analyze the different gestures of a human hand. Unlike the different possible actions with a hand, the number of postures of the hand is limited. In that sense, MacKenzie and Iberall [21] proposed six different grasping postures which are: cylindrical grasp, tip, hook, palmar, spherical grasp and lateral. From those postures, two important parameters must be taken into account in the data glove design. The parameters are the object shape and the surfaces of the hand participating in the grip. To obtain information on the object shape, we need to know the angle of each phalanx compared to the previous. Thus, we used bending sensors placed on the distal and intermediate phalanx to get this information (shown in red in the Figure 1). Then, to study the kinematic of a finger, we need to know the bending angle between the finger and the back of the hand. Thereby, we placed another bending sensor on the proximal phalanx and the metacarpal (shown in green in the Figure 1). However, these two bending sensors per finger is not enough to perceive the presence of an object in the hand. Thus, among the surfaces of the hand participating in the grip, we have to place a force sensor on each terminal point of the fingers (shown in blue in the Figure 1).

According to the actual sensors and devices available on the market, we selected for the force and bending sensors the Flexiforce A201 sensor of Tekscan (~18$) and the Flex Sensor 2.2 (~8$) respectively. Both sensors must be connected to the Voltage and the ground in order to work properly. Also, to get the data from these sensors, we connected them to the analog ports of an Arduino Mega 2526 (~29$) with a resistance of 10k (~0.10$) between each sensor and the microcontroller. The Arduino Mega 2526 has been chosen because of its number of analog ports which is 16. Indeed, according to the number of sensors, we need at least 15 analog ports. The electric schema is illustrated in Figure 2. In addition, to avoid any problem of connection, we replaced the breadboard with a printed circuit board as illustrated in Figure 3. Finally, the prototype of the data glove is illustrated in Figure 4. The total cost of the prototype by adding the glove, the cables and the tape is approximately 220$ in USD.

4. Recognition

The system described in the previous sections represents the data glove used to acquire the data provided by the sensors. These data are related to daily basic activities such as *hold a spoon*. The conventional name given to that information is raw data. Thus, in order to achieve a daily basic activity recognition, the raw data are processed by extracting features before to use them for the classification stage with machine learning algorithms. This section presents in detail the features extracted from the signal, and the selected machine learning algorithms to recognize the daily basic activities.

4.1. Feature Extraction

In this work, the selected features to compute from the raw data have been chosen according to the nature of the signal. Indeed, the signal is defined as stationary. The problem of this type of signal is that the number of possible features is limited. Thus, we opted for 2 well-known features from the time domain: the mean $Mean = \frac{\sum_{k=N-10}^{N} x_k}{10}$ and the standard deviation $Std = \sqrt{\frac{1}{10}\sum_{k=N-10}^{N}(x_k - Mean)^2}$, where x_k is the sample k acquired by one of the sensors and N denotes the last sample index in the time windows. The features are extracted by using a time windows defined by a length of 1 second with 50% overlapping over each raw data of the sensors. In addition, the frequency of the data acquisition is 10Hz (10 samples per second). Finally, by extracting those two features for each sensor, we obtain a feature vector of 30 components.

4.2. Machine Learning Algorithms

Once the discriminating features extracted from the raw signals are determined, the recognition of the daily basic activities can be processed. According to the literature in the domain of activity recognition, several algorithms have shown their efficiency in this field of research such as : Decision Trees (e.g. : C4.5, CART), Support Vector Machine

(SVM), k-Nearest Neighbors (k-NN), Naive Bayes, Hidden Markov Model (HMM), Random Forest (RF) [9]. In that sense, we decided to exploit the k-NN and the Random Forest algorithms which are both non-parametric methods. Those algorithms remain simple to implement and to use, powerful and efficient.

4.2.1. k-NN

The k-Nearest Neighbors (k-NN) [16] is the simplest classification algorithms. k-NN is defined as a non-parametric lazy learning algorithm. In other terms, any model is computed. However, the algorithm needs all training dataset for the classification process of a new instance. This results into costly processing time when the number of occurrences is very large. This method relies on determining the k nearest neighbors among all the training dataset of the new observation x by computing distances between x and each training data. Then, the new instance gets the label (class) y of the predominant category among the k nearest neighbors. The user selects the number k of nearest neighbors and the type of distance (Euclidean distance, Chebyshev distance, etc.) [16].

4.2.2. Random Forest

A Random Forest (RF) is a supervised machine learning algorithm proposed by Breiman in 2001 [6]. It presents the advantages to be simple, flexible and efficient. Indeed, a RF is a combination of decision trees, where each tree is constructed by using a random vector of values (sampled independently with the same distribution). Thus, the algorithm can be modelled by a forest of random trees. The final classification is given by a majority vote between each decision of each tree. For such an algorithm, the user must set parameters, which are the number of trees in the forest, the number of features to consider for the best split, and the measurement function to determine the quality of the split (Entropy, Gini) [6].

5. Experiments

The experiments we have conducted involved 5 participants described in the first point of this section. Then, in the second point of this section, we detailed the procedure of the data acquisition that each participant had to performed.

9 recruited participants were apt to perform the experiments. Indeed, the data glove has been designed for people with large hand. All the participants are males, aged from 23 to 39 years old and were healthy persons without any hand dysfunction.

The objective of this research is to design a data glove and prove the concept that we can recognize objects with this one. To this end, it was essential to define the type of basic activities that our participants can perform in order to validate the accuracy of our system. Thus, we selected 7 common objects in a kitchen that can be held by a hand and the empty hand action. The list of the basic activities is :*1 - Hold a plate, 2 - Hold a cup, 3 - Hold a spoon, 4 - Hold a knife, 5 - Hold a fork, 6 - Hold a pot, 7 - Hold a pall, 8 - Empty hand*. For each basic activity, the object must be held from the beginning to the end of the data acquisition. Also, to create a significant dataset, the duration of the data acquisition is 10 seconds. During this time, the participant can perform all the movement he wants with the object in its hand. We reproduced 5 times this experiment for each object and for each participant.

6. Results and discussion

6.1. Classification Performance Metrics

It is known that the classification task requires to be properly evaluated with some well-known performance metrics. To this end, we decided to express the performances of the daily basic activity recognition with the accuracy (Acc.), Kappa measure (k), F-Score (F), precision (P) and the recall (R) [5]. The accuracy is probably the most popular metric because of its simplicity. This performance measure provides the ratio between the correct number of predictions and the total number of occurrences. Unfortunately, this performance metric alone does not provide enough information to evaluate properly the classification model and the robustness of the prediction. Indeed, it exists a paradox related to this metric called the accuracy paradox. For instance, in a case of unbalanced dataset between two classes, the number of occurrences in one class is enough high to improve the accuracy by always predicting TP. According to this paradox, we decided to exploit the Cohen's kappa (k) evaluation metric as suggested by Ben-David [5]. This performance measure considers the possible effect of an unbalanced dataset on the accuracy.

6.2. Results

The performance for the daily basic activity recognition through the raw data produced by the data glove that embed 15 sensors was evaluated according to two machine learning algorithms. Also, to generate predictive models, we need a training dataset. Thus, we decided to use the traditional 70-30 to divide our data (70% for training and 30% for testing).

First, the k-NN algorithm has been tuned according to the number of neighbors k and the type of distance to compute between the new instance and the data. With an experimental approach, the value of $k = 5$ gives the best performance with the classic Euclidean distance.

Second, the RF classification algorithm has been tuned according to the number of trees in the forest T and the number of randomly picked features N for each tree in the forest. As suggested by the literature [7], the number of features for each tree that we selected is $N = \sqrt{m}$, where m is the total number of features extracted from the raw signals. Then, we arbitrary chosen $T = 100$ trees. Table 2 and Table 3 show the performances for the k-NN and the RF algorithm respectively.

Table 2 and Table 3 show the performances for the k-NN and the RF algorithm respectively.

Table 1. Object recognition with k-NN, 70-30.

k-NN, $k = 5$, Euclidean distance, 70-30				
Global Accuracy	0.94			
Global Cohen's Kappa	0.94			
	P	R	F	Support
Hold a plate	0.9960	0.9880	0.9920	251
Hold a cup	0.9246	0.9510	0.9376	245
Hold a spoon	0.9427	0.9030	0.9224	237
Hold a knife	0.9098	0.8657	0.8872	268
Hold a fork	0.8992	0.9612	0.9292	232
Hold a pot	0.9835	0.9715	0.9775	246
Hold a pall	0.9395	0.9902	0.9642	204
Empty hand	0.9600	0.9375	0.9486	256

Table 2. Object recognition with RF, 70-30.

RF, $T = 100$, $N = \sqrt{30}$, 70-30				
Global Accuracy	0.99			
Global Cohen's Kappa	0.99			
	P	R	F	Support
Hold a plate	1.0000	1.0000	1.0000	251
Hold a cup	0.9796	0.9796	0.9796	245
Hold a spoon	0.9957	0.9873	0.9915	237
Hold a knife	0.9703	0.9739	0.9721	268
Hold a fork	0.9744	0.9828	0.9785	232
Hold a pot	0.9959	0.9959	0.9959	246
Hold a pall	1.0000	1.0000	1.0000	204
Empty hand	1.0000	0.9961	0.9980	256

We can see in Table 1 and 2 that the object recognition is almost perfect with both algorithms. However, we can conclude that the RF algorithm is better than the k-NN algorithm. Finally, the two objects with the minimum score are the knife and the fork. Indeed, it exists some *hold a fork* instances that are predicted as *hold a knife* and vice versa. This is due to the very similar way that the knife and the fork are grasped. Nevertheless, the differentiation between them is excellent in general.

Due to the exceptional results in Table 1 and 2 and to avoid any overfitting effects, we decided to use only 20% of the data as the training dataset and 80% of the data as the testing dataset. Table 3 and 4 present the results of the k-NN and the RF algorithm respectively.

The results of the object recognition are still excellent for the RF algorithm, even if we can observe a global decrease of the recognition for each object. Also, the confusion between the knife and the fork is accentuated due to the low number of occurrences describing the actions *hold a knife* and *hold a fork* in the training step of the machine learning algorithms.

Finally, we achieved a last test to determine if our system can be generalized to other persons without any training step of the machine learning algorithms. In this test, we have taken the overall data of eight participants for the training dataset, and the data of the ninth participant represents the testing dataset. This method is called leave one out. To do so, the RF algorithm has been selected. Figure 5 shows the confusion matrix of the predicted labels (object) versus the true labels for one participant.

Table 3. Object recognition with k-NN, 20-80.

k-NN, k = 5, Euclidean distance, 20-80				
Global Accuracy	0.89			
Global Cohen's Kappa	0.88			
	P	R	F	Support
Hold a plate	0.9772	0.9670	0.9721	666
Hold a cup	0.8527	0.9276	0.8886	649
Hold a spoon	0.8650	0.8995	0.8819	627
Hold a knife	0.8350	0.7389	0.7840	678
Hold a fork	0.8062	0.8583	0.8314	635
Hold a pot	0.9717	0.9250	0.9478	667
Hold a pall	0.8934	0.9554	0.9233	605
Empty hand	0.9412	0.8709	0.9047	643

Table 4. Object recognition with RF, 20-80.

RF, T = 100, $N = \sqrt{30}$, 20-80				
Global Accuracy	0.95			
Global Cohen's Kappa	0.95			
	P	R	F	Support
Hold a plate	1.0000	0.9955	0.9977	666
Hold a cup	0.9181	0.9676	0.9422	649
Hold a spoon	0.9562	0.9410	0.9486	627
Hold a knife	0.9206	0.8717	0.8955	678
Hold a fork	0.8880	0.9118	0.8998	635
Hold a pot	0.9863	0.9700	0.9781	667
Hold a pall	0.9902	1.0000	0.9951	605
Empty hand	0.9659	0.9689	0.9674	643

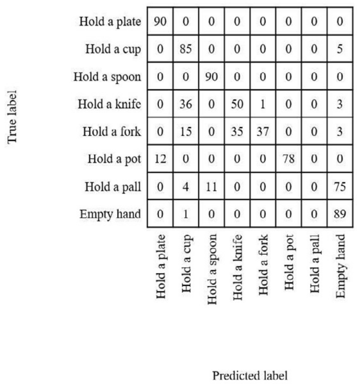

Fig. 5. Confusion matrix of the object recognition for one participant versus all.

We can see that the predicted model does not perform well the object recognition. Indeed, the global accuracy and the Cohen's Kappa in this case are only 0.72 and 0.68 respectively. However, we can see that the way to hold a plate, a cup, a spoon and a pot is similar to the eight other participant. The explanation of these results is that two different persons can hold an object differently compared to other persons.

Thus, we can conclude that the data glove prototype performs well the object recognition when the system has been trained with the same participant than the one who tests the data glove. In other terms, the data glove has to be beforehand trained by the patient to be exploited in a basic daily activity recognition. In addition, in order to generalize the prediction model, we have to train the model with a large number of persons to be efficient in the object recognition with a new person.

7. Conclusion

In this work, we proposed a new prototype of data glove which is simple and cheap (~220$ in USD). Also, the simplicity of the signal processing and the machine learning algorithms exploited represents a real advantage. Indeed, the proposed approach allows to perform well the object recognition for basic daily activities. Also, the performances presented in this study are almost perfect since the accuracy and the Cohen's kappa are closed to 100%. This result is surprising and encouraging considering the low sample rate (10Hz) and the number of features extracted. Thus, we provided a simple, cheap, reproductible and efficient data glove for object recognition by abstracting all the theory of gesture recognition. In real-life conditions, such a device could be really useful to monitor the evolution of the dysfunctionality of the hand in a case of Alzheimer disease. Also, given by a therapist to a patient, this device can be used in the comfort of their home. It can recognize object, and consequently, the common daily activities such as *cook pasta* or *make a coffee*. Finally, even if the prototype induces great results, it could be really interesting to improve the data glove hardware by adding some other force sensors and a 9 axis Inertial Measurement Unit. Indeed, the integration of these optional sensors could improve the generalization of the proposed system.

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