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Hand Gestures Identification for Fine-Grained Human Activity Recognition in Smart Homes

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Abstract

Most developed countries are facing important demographic issues related to ageing populations. Maintaining elders at home while ensuring their safety and well-being often constitutes the main goal of these countries. An interesting solution to this challenge is to develop a smart home, able to monitor the routines of the resident, to recognize the on-going activities, and to provide support when required. In the literature, most works focus on monitoring high-level behaviors such as eating, sleeping, etc. However, to provide live guidance, the system needs to have a far more detailed recognition process able to identify the specific steps of the on-going task and the erroneous executions. In this paper, we propose an algorithmic approach for hand gesture recognition designed to be used as the core component of a fine-grained activity recognition model. It is based on the processing of inertial data collected from a wristband equipped with triaxial accelerometer and gyroscope, and machine learning techniques. A simple set of gestures for cooking activities as been defined, enabling characterizing high-level cooking tasks. To do that, we constructed a labelled dataset of atomic gestures performed by participants that we made available to the scientific community. We obtained an average accuracy of 0.83 in recognizing the gestures with the leave-one-subject-out strategy.

Keywords: *Smart Homes, Fine-Grained Activity Recognition, Hand Gesture Identification, Assistive Technology*

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1. Introduction

Western countries are currently experiencing an unprecedented demographic crisis linked to the accelerated ageing of their population [1]. This reality is worsened by a problem of a general labor shortage [2], particularly with regard to qualified personnel in the medical field, and more specifically for home care dedicated to people with loss of autonomy. Seniors suffering from a loss of autonomy wish to remain at home [3]. Governments are pushing for this for both social and economic reasons. In fact, keeping elders at home longer is clearly desirable because it contributes improving the quality of life, which corresponds to societal values: people should live as normal a life as possible without segregation in retirement homes. However, keeping seniors with loss of autonomy at home involves many risks that need to be controlled. The physical environment of residences must therefore be adapted, or even increased with the help of technology and artificial intelligence, in order to meet elders' needs, to compensate for cognitive and physical disabilities, to ensure safety and to adequately support residents in carrying out their Daily Living Activities (ADL) [4].

It is in this specific context that, around the world, a community of scientists [14-16] is actively seeking technological answers to this problem through the concept of Smart Homes (SH) [5]. It refers to the concept of enhancing a house with a set of sensors and actuators integrated to several everyday objects (cabinet doors, stove, lamps, etc.), as transparent as possible. These devices aim to monitor the person's behavior, provide assistance to the user and support to family and caregivers based on the information collected and the history of accumulated data. This type of service is relevant because it is intelligent (detection of the need) [6], it is adapted (user profile) [7] and it is always available everywhere in the home (ambient) [8]. A solution often proposed to this problem is to provide fully automated systems which take over the task of the user. However, this approach largely restricts the autonomy, motivation and interest of the person and tends to accelerate cognitive degeneration [9]. The alternative that many teams recommend is to provide an assistance system (as opposed to an automated system), which is able to follow, in real time, the activities of a person with loss of autonomy and suffering from cognitive disorders, to identify her erroneous or risky behaviors, and to provide adequate instructions (advice, suggestions or reminders), allowing the situation to be corrected [10]. The system can nevertheless perform a direct intervention (e.g., turn off the power supply to the stove), but only in an emergency situation or when guidance fails. The objective is therefore to provide on-demand assistance based on information collected in real time by the sensors and the history of accumulated data. This type of system keeps the person in cognitive stimulation, which with personalized and adequate assistance supports him in his autonomy and helps him to complete the majority of his activities, while ensuring his safety [7].

In this paper, we propose an algorithmic approach for hand gesture recognition specifically designed to be used as the core component of a fine-grained activity recognition model enabling such assistive technologies. In the next sections, we show how we addressed the issue of granularity using accelerometers and gyroscopes on a wristband to characterize different cooking gestures into a set of adaptive actions specific to certain activities, drawing inspiration from the work of [18]. Thus, the analysis of ambulatory movements of hand gestures is associated with a precise pattern of gestures forming a set corresponding to fine-grained activities. More specifically, we will show how we constructed a fully labelled dataset serving as basis for learning atomic gestures.

2. The Problem of Fine-Grained Activity Recognition

In the scientific literature, the main problem [11-14] inherent in the development of assistive technologies adapted for home care concerns artificial intelligence models allowing real-time recognition of a person on-going ADLs (preparing a meal, washing hands, taking medication, etc.). Generally speaking, the problem of ADL recognition in smart homes relates to a fundamental question in AI [15]: how to identify the actual on-going activities, as well as their progress (steps), so that this identification can be used in a decision-making assistive process? Typically, a recognition system takes as input a sequence of observations (low level inputs coming from sensors), performs an interpretation of these inputs (extraction and interpretation of that information) and then applies an algorithm allowing to match the observed inputs sequence with one of the activity models (signature) contained in a knowledge base. Most existing approaches suffers from an important limitation because they target a very low granularity [17], meaning they only allow to identify between large categories of activities (morning routine, washing, preparing a meal, etc.). The reason is that most of research have previously focused on monitoring the user's routines and learning patterns in those routines, instead of focusing on on-line assistance. This is the case, for example, of the well-known works of professor D. Cook' and her team from Washington State University [20-22]. Her team worked for more than a decade on the ADL recognition problem from multiple angles. They proposed a lot of approaches for recognizing high-level ADL from low-level ambient sensors using *Decision tree classifier* (DT), *Naïve Bayes Classifier* (NBC), *Random Forests* (RF) and *Support Vector Machine* (SVM) [20]. They also worked on the issue of multi-resident ADL recognition [21]. Recently, they tackled a bit the problem of fine-grained activity recognition by introducing a new approach for precisely identifying the beginning and ending time of an activity [22]. This new information is very useful since the time, delay, and orders of the activity is meaningful. However, they did not address the problem of very specific low-level actions (steps) recognition. However, it is still insufficient to provide guidance. Recently, some works tried to address the specific issue of recognizing low-level actions in smart homes and hand gestures [23-25]. For instance, *Dinh et al.* [23] proposes recognizing the hand parts in a depth hand silhouette using a camera-based system. His team created a database (DB) of synthetic hand depth silhouettes and their corresponding hand parts labelled maps and then trained a *Random forest classifier* with the DB. They got interesting results, but the approach is limited in the precision of the information (only hand parts are recognized and not the action done by the hand) and also by the use of cameras. Elders are often very reticent to the use of camera in their homes. It is why we took an approach based on a wearable wristband. More recently, *Purushothaman* et al. [24] proposed an approach like us. They used a wearable device with accelerometers and gyroscopes to sense and capture tilting, rotation, and acceleration of the hand movement. Four different hand gestures are captured using this wearable device and machine learning algorithm namely SVM has been used for classification of gestures with the aims of controlling ON/OFF of appliances. While their proposition is good, they only recognize four primitive gestures: up/down, hand rotation, right-left, and z-movement of the palm. This is not enough to enable high-level activity recognition as we intended. Another example is the work of *Savaridassan et al.* [25] that proposes a hand gestures recognition system based on three accelerometers (but no gyroscope), communicating with ZigBee transmission module, using a simple segmentation algorithm. The purpose of the system is to detect activation commands for the fan, the light, and the central heating. Like other works, the recognized gestures are too limited to be adequately used for fine-grained activity recognition.

3. Hand Gesture Recognition Approach for Fine-Grained Activity Recognition

We propose, in this section, an algorithmic approach for hand gesture recognition. It relies on the processing of inertial data collected from a wristband with a triaxial accelerometer and a triaxial gyroscope. The first step of our project, and one of the main contributions of the paper, was to create a labelled dataset of simple cooking gestures from which high-level cooking tasks can be defined. To do that, we constructed a fully labelled dataset of 13 atomic gestures that we made available[1] to the scientific community. We hope to achieve the detection of these basic gestures with the help of machine learning techniques and the use of a custom wristband, previously conceived, made, and extensively tested in our lab by [19]. In Table 1, one can see what we call *slow gestures* (SG), which correspond to gesture that can be completed within 3 seconds.

The wristband worn by the participant is wirelessly connected to a Raspberry Pi 3[†] using Bluetooth Low Energy (BLE) that collects the wristband's data at a sampling rate of 60 Hz. Then, a computer, connected to the Raspberry Pi 3 using the lab's local WI-FI network is used to retrieve the wristband's data via a WebSocket. Next, in Table 2, we present what we characterized as *fast gestures* (FG), which can be performed within a second:

† https://www.raspberrypi.com/products/raspberry-pi-3-model-b/

Table 1. Title, definition, and representation of slow gestures (SG).

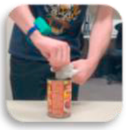
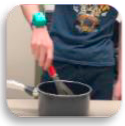
Salt[‡]: a simple gesture of pouring salt at a relatively normal speed. The gesture contains repetitions during the captured window as it is considered like a continuous gesture.	
Pour: the act of pouring about one cup of liquid into a bowl. The focus of the gesture is when liquid is poured but we could also take the lifting and lowering of the mug into consideration to get to the desired time window.	
Roll: contributors used a rolling pin on play dough to simulate the movement of flattening a real dough. Results were achieved using a continuous motion.	
Egg: for this action, we consider the breaking of the egg and its pouring into the bowl. A tea ball is used to replace the egg.	
Can: the gesture represents the act of using a can opener to open a real can, captured on a continuous frequency.	
Drink: the main movement sought was the action of drinking, but with a time window of 3 seconds, the action was done in three steps: raise the container, drink, lower the container. This container was a coffee mug (the same one used for the pouring action).	
Flip: the gesture simulates a pancake or omelette spin. A spatula was used along with a mouse pad. The last two participants made the gesture with a pancake-shaped dough (similar in weight and consistency).	

Table 2. Title, definition, and representation of fast gestures (FG).

Whip: a continuous gesture where participants used a whisk and a bowl of water. The goal was to whip the same way the participants would've done in a real situation.	
Walk: this next gesture consisted of a participant walking in a perpetual motion to simulate a walk in the kitchen.	
Grate: participants used modelling clay to simulate the action of grating cheese at a continuous pace.	
Mix: participants mixed water in a container with a spoon over a continuously determined amount of time.	
Idle: for this gesture, applicants were asked not to move at all. They were usually in a relaxed standing position.	
Cut: the action of cutting was done with a knife and clay. The gesture was done in a continuous way.	

3.1. Building the Gestures Dataset

The key for developing an accurate recognition system is the quality of the learning data. It is why constructing a precise and complete dataset is such an important part of the project. We designed a rigorous experimental protocol§ to ensure the quality of the data. The protocol can be summarized as follow: 1) each participant is asked to put on the wristband; 2) one member of the team tests the system and the data acquisition pipeline with a few practice gestures; 3) when all the devices are synced and practice tests successful, we start filming the participant using a mobile phone and we start the acquisition program at the same time; 4) the participant is asked to make a quick gesture at the beginning of the video (before starting his/her predetermined gesture) to help clearly visualize and

‡ Gestures' titles are shown in *underlined italic*.

[1] *https://github.com/LIARALab/Dataset-Hand-Gestures-Identification.git*

§ *Data collection was conducted under ethical certificate under file number UQAC-2021-487.*

identify a temporal point for the synchronization (seen later in Fig. 1); and 5) the participant can now start a gesture, like seen in Table 1 or 2.

Each hand gestures were performed and filmed in the controlled environment. Each participant was asked to perform at least 20 repetitions of each gesture (10 for each hand). For both hands, participants wore the wristband at the same location on the wrist and in the same orientation. This protocol allowed us to gather inertial data from each different gesture repetition performed by the 21 participants in csv files.

Gestures were labelled using a custom annotation program (see Fig. 1). This one went as follows: first, we had to load the video of the desired gesture and its corresponding csv file. Then, it was necessary to synchronize the two with the “sync video” and “sync data” button. For that matter, participants were asked to make a quick movement at the beginning of the video to help clearly visualize and identify a temporal point for the synchronization. By using the program, we could add a label (from a list of gestures) at the start of each atomic movement. When all the gestures were annotated (labelled in a single file), the software exported a file like the input csv file, but this time with labels at the specific timecode rows of the gestures’ beginnings. The procedure was repeated with all the previously created participants’ files.

Thereafter, 17 features for each 6 axes of the input data, starting from the labelled rows, corresponding to each tags’ time window were extracted. At the end, it created a new dataset of 102 columns (attributes) and *n* rows, where *n* is the total number of annotated (labelled) gestures. Table 3 shows a list of the extracted features.

Table 3. Extracted features for each axis of the data.

Minimum	Maximum	Average	Median	Standard deviation
Skewness	Kurtosis	Mean absolute deviation	Waveform length	Zero crossing rate
Mean crossing rate	Squared Energies	PSD entropy	Energy of the detailed coefficients of the 3-level discrete wavelet transform	

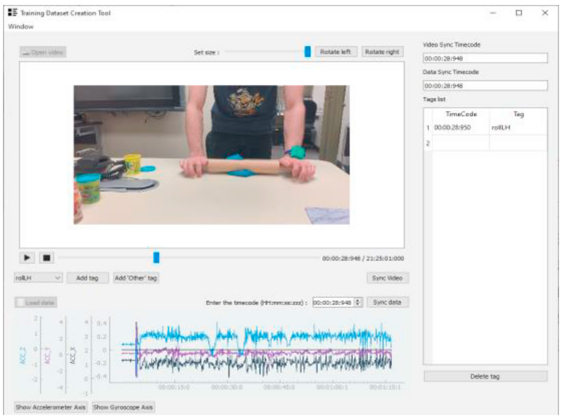


Fig. 1. Screenshot of the annotation program.

The protocol has been used for the construction of different datasets that, as mentioned earlier in the paper, are available online. The next section details how we used this new carefully labelled dataset to develop an algorithmic approach for hand gesture recognition.

3.2. Learning Hand Gestures from the Dataset

Having a clean dataset with newly extracted features allowed us to apply a supervised learning approach to a multiclass classification problem. First, we loaded the previously created data, then separated the data into a training dataset (70%) and a testing dataset (30%). A *MinMaxScaler* was then applied to the training and testing attributes. We incorporated the slow gestures (SG) in the fast gestures (FG) dataset as the class labelled *other* because it was possible to shorten the time window of the slow data (3 secs. > 1 sec.). However, the opposite was not viable, as we did not record FG for more than a second, and thus, 1 sec. cannot stretch to 3 secs. For the SG dataset, walk and idle were labelled as *other*. This data preparation process was performed two times, one for the slow gestures, and another time for the fast gestures. At this stage, there were 5668 slow gestures and 939 fast gestures for a total of 6607.

4. Experiment and Results

As mentioned in the previous section, we obtained 5668 slow gestures and 939 fast gestures following the data preparation process. The main objective of this study is to classify these gestures correctly. Hence, we need to determine a good classifier to perform this task. To do so, we selected 7 classifiers, which are: *Classification And Regression Trees (CART)*, *k-Nearest Neighbors (k-NN, k = 5), Random Forest (RF)*, *Naïve Bayes (NB)*, *Support Vector Machine (SVM, decision_function_shape = ovr, kernel = rbf)*, and *Multi-Layer Perceptron (MLP, hidden_layer_sizes = (100,), activation = relu, solver = adam)*. The reason why we selected these classifiers is that they are mathematically different and can have a significant difference in the classification performances. In addition, we scaled each feature of the dataset by using the *MinMaxScaler* function from scikit-learn [19], where the minimum and maximum values of each feature are used for this transformation. This transformation is necessary because we are comparing classifiers, where some exploit geometric distances. In other terms, the classification performances of this kind of classifiers vary greatly with the magnitude difference between datasets' features. In addition, we used the *SelectKBest* algorithm to reduce the number of features. Reducing the number of features also reduces the risks of overfitting of the trained model that we could encounter with the split 70-30 and k-fold cross-validation strategies. Here, we selected 50 features using the Chi-squared to compute importance scores. This value has been determined graphically according to the importance scores. In Table 4, we present the classification scores for each classifier obtained from the SG dataset. We carried out the 10-fold cross-validation for classifiers' training and testing stages. As illustrated in Table 4, we can observe that RF and MLP classifiers have the highest classification scores. Indeed, RF and MLP classifiers reached 0.93 and 0.94 for the F1-score, respectively. Also, we know that the RF classifier has better properties for generalization [26]. In other terms, an RF classifier is better to handle noise in data than a simple MLP classifier. Thus, we decided to adopt the RF classifier for the rest of our experiments, including those from the leave-one-subject-out (LOSO) strategy.

Table 4. Average performances of different classifiers on SG using 10-fold cross-validation.

Algorithm	F1-score	Accuracy	Algorithm	F1-score	Accuracy
CART	0.84	0.84	NB	0.76	0.76
k-NN	0.91	0.91	SVM	0.89	0.89
RF	0.93	0.93	MLP	0.94	0.93

After we selected the RF classifier, we proceeded to a grid search to determine one of the best sets of hyperparameters for this classifier. Fig. 2 shows the confusion matrix and the classification report resulting from the grid search for the SG dataset, where the determined set of hyperparameters was: tree_number=100, max_depth=25, criterion='gini'. We carried out the split 70-30 for the successive classifier's training and testing stages.

We can observe in Fig. 2 that all activities have an F1-score superior or equal to 0.91, except for *can* and *egg* (breakEgg). Indeed, the *can* activity is mainly confused with *egg* and 14 instances of the *mix* activity have been confused with *can*. Also, a few instances of other activities have been confused with the *egg* activity. We think that the confusion is mainly related to participants' force in breaking the egg or micro-movements when mixing water in a container. It should be mentioned that for the FG dataset, the results are outstanding. Indeed, we got an F1-score superior or equal to 0.95. The main reason is that we only have two classes for the FG dataset.

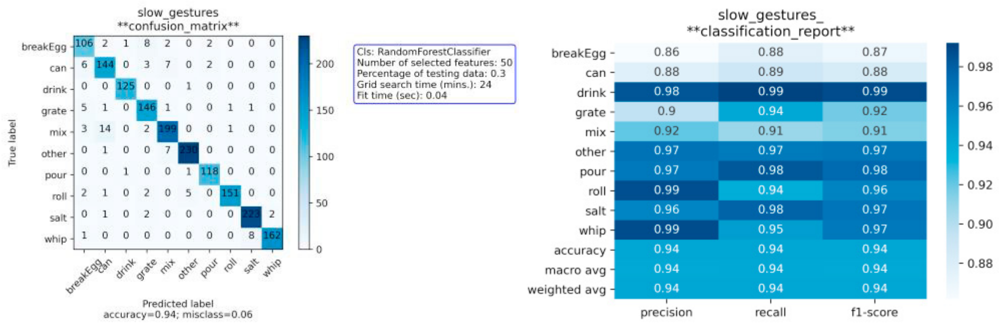


Fig. 2. (a) SG confusion matrix; (b) SG classification report.

Due to the excellent results obtained from the grid search and the split 70-30, we decided to explore the classification performances deeper by exploiting the LOSO strategy. This strategy is often used to observe the classification performances obtained in real conditions. In other words, this strategy allows observing the properties of generalization of the classifier. Hence, we train and test the classifier *N* times, where *N* corresponds to the number of participants. More specifically, we left out one participant to test the trained model, which is different each time. Table 5 compares the classification performances obtained with the LOSO strategy on the full SG dataset and the reduced SG dataset.

Table 5. Classification performances on the full and reduced SG datasets obtained with the LOSO strategy.

	Full SG dataset				Reduced SG dataset with SelectKBest algorithm			
	Accuracy	F1-score	Precision	Recall	Accuracy	F1-score	Precision	Recall
Worst	0.66	0.66	0.68	0.66	0.56	0.51	0.53	0.56
Average	0.83	0.82	0.85	0.83	0.75	0.74	0.78	0.75
Best	0.97	0.97	0.97	0.97	0.88	0.87	0.9	0.88
Std	0.07	0.08	0.08	0.07	0.09	0.1	0.09	0.09

The results in Table 5 are surprising. Indeed, we thought that we would get the best classification results by applying the SelectKBest algorithm. However, it is not the case. Instead, we obtained an average accuracy of 0.83 and 0.75 for the full SG dataset and the reduced SG dataset, respectively, corresponding to a significant difference of 8%. Also, the difference is 9% between the two datasets for the maximum accuracy. To better understand the variation of the results, we also observed the confusion matrices. For most participants, the *egg* and *mix* activities have the worst performances. This is because they are mostly confused between them and the *can* activity. We also observed that the *salt* and *whip* activities are confused between them and the *grate* activity. Although the activities seem very different in the execution, we think that micro-movements can greatly influence the classification.

Finally, we also look at the classification results using only left or right-hand gestures. In other terms, we divided each dataset (SG and FG) into two new datasets defined by the hand that made the gesture. All classification results were superior or equal to 0.93 for the F1-score, except for the SG dataset's right-hand gestures, where we only reached an F1-score of 0.81.

5. Conclusion and Future Works

In this paper, we proposed a model for hand gesture recognition designed to be used as the core component of a fine-grained activity recognition system. It relies on a wristband with a triaxial accelerometer and a triaxial gyroscope. We defined a set of gestures for cooking activities, which allows characterizing high-level cooking tasks as a set of simple gestures. One of the main contributions of our work is the construction of a carefully labelled dataset of 13 gestures gathered from 21 participants using a rigorous experiment protocol. This dataset has been made available to the scientific community. Each participant performed each gesture a minimum of 20 times. The system showed good results with an average accuracy of 0.83 in recognizing the targeted atomic gestures with the LOSO strategy. Also, these results are promising for developing a complete fine-grained cooking activities recognition model. In future works, we plan to add a mechanism that prioritizes certain types of gestures in case of multiple simultaneous recognition. For instance, a fast gesture of one second, or two, can be recognized in the same three seconds window in which we could also have recognized a slow gesture. In that case, we need to discriminate. Moreover, the atomic gestures recognition system could be enhanced with ambient sensors. Finally, we also plan to extend the actual system using RFID sensors to approximate the 2D position of the hand in the room versus the actual position of different detectable objects.

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