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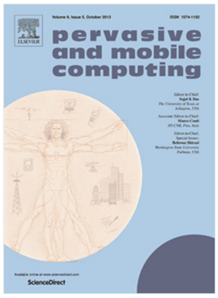

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Identifying Users from the Interaction with a Door Handle

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Abstract

Ambient intelligence pursues the integration of intelligent approaches on an IoT infrastructure, mainly using everyday objects of the environment. The main hypothesis of the work is that the way in which a user interacts with a door handle is suitable to be used in the identification task. Our proposal contributes with a new method to identify persons in a seamless and unobstrusive way, suitable to be used in a smart building scenery without the need to bring any aditional device. In this case, we embed accelerometers and gyroscopes in a door handle in order to obtain a data set comprising samples of 47 individuals. A parametric approximation is adopted to reduce each sample to a feature vector by using a dynamic time warping technique. A study has been made of the outcomes of different classification techniques over six different feature sets in order to assess the feasibility of this identification challenge. The AUC values observed with the selected feature set show promising results above 0.90 using neural networks and SVM classifiers.

Keywords: Ambient Intelligence, User Identification, IoT, Sensors, Pattern Matching, Access Control

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1. Introduction

The impact of the Ambient Intelligence (AmI) on our daily life appears at the very moment in which we use any everyday object, such as a light switch or a water tap equipped with a blend of technologies that comprises the Internet of Things (IoT), and delivering a solution that incorporates intelligence to its operation. Every device of this kind blends technologies like Radio Frequency Identification (RFID), Near Field Communication (NFC), wireless communications, real-time location and sensor networks, with Artificial Intelligence (AI), so things become smarter and do more than they were proposed to.

In relation to what could be expected within a smart city environment, this is concretised in the usual interaction of people with the elements such as a light switch, a mailbox, and a door through small actions where the context plays a main role.

According to [1, 2] AmI is supported by computing and networking technology embedded in all kinds of objects in the environment that are sensitive and responsive to the presence of individuals. In fact, the computing infrastructure becomes transparent for the user which does nothing but interacting with the usual objects that are the last link of an AmI enabled system. The analysis and identification of the human activities is a main interest of research within the AmI discipline. According to [3] there are various types of human activities depending on their complexity: gestures, actions, interactions, and group activities. Whereas *gestures* are the atomic components of the motion of a person, which forms an *action* when combined, *interactions* involve objects with two or more people. The presence of conceptual groups composed of multiple persons and/or objects define a *group activity*. Nevertheless, other classifications of human activities are based on the duration of the action. For example, in [4] an action is defined as a simple motion pattern usually involving a single person and lasting a shorter time, typically on the order of seconds, whereas an activity refers to a complex sequence of actions performed by possibly several humans with a longer duration.

Furthermore, one of the main interests in the analysis of human activities is the possibility of identifying the person who is performing the action. This identification is the base of AmI applications where the answer of the system to an implicit input depends on the identity of the human who is making the action, as for example in a building or even a room climate control access.

In this paper, we present a novel and completely transparent system for automatic person identification based on the interaction of a person with the handle of a door, when he/she tries to open the door, without the mediation of any extra device brought of worn by the user. Regarding the classification of human activities referred above, we consider this to be a micro-action, given that this can be defined as an atomic part of the more general action "open a door" and its temporary duration is only of a fraction of a second.

2. Related Work

Doors are one of the most commonly used things in premises, with many uses per person each day [5]. Usually the capability of opening a door depends on the identity of the individual and the answer to this question: "*Should this person be given access to this place?*".

Traditionally, the identification of a person trying to open a door can be based on an information challenge, a token or a biometric measure.

In an information challenge based identification, the individual must show that he/she knows a shared secret, as a password or PIN, for example.

In the token-based identification methods, the user must present a physical credential or token. The presence of this token must be demonstrated by using it to interact with the access control of the door, i.e. a key, an RFID tag [6] or NFC device [7].

These two categories of access control mechanisms are far from being considered transparent from the user point of view because they force an explicit interaction with the access control prior to the act of opening the door. Our proposal pursues the elimination of the previous interaction with the access control device, in an AmI environment, when a user tries to open a door, in a seamless and transparent way.

Biometrics refers to the automatic identification of a person based on his or her physical or behavioural characteristics. Face, eye, hand, finger geometry and the speech recognition are some of the most usual technologies for static biometrics [8]. Some of them are currently used in access control for doors, but all of them lacks the necessary transparency we pursue, because they need an explicit interaction with the system to allow the identification, i.e. waiting in front of a camera to be recognised, speaking to the system or laying the finger on a fingerprint scanner. The accuracy of these identification methods varies notably. In [9], Al-Sebani *et al.* review the results of several works regarding door access control systems based on face recognition that reports a recognition accuracy in the interval from 85% to 96%. The possibilities of speech recognition in access control purposes have also been researched. In this line, Kayode *et al.* show in [10] a voice-activated door control system with an accuracy of more than 80%. Similar results have been reported in [11]. The use of the fingerprint in control access systems has been considered for a long time a reliable biometric feature, being not difficult to find fingerprint based commercial systems. In one research conducted by Mittal *et al.* [12] about the recognition accuracy of a fingerprinting device as a person-specific door access control, it was obtained a recognition accuracy close to 90%. Along with the fingerprints, the finger-vein can be used also as a biometric element to identify people. In this line of research, in [13] Ko *et al.* show a recognition algorithm that is able to obtain an accuracy of 97% based on grey images of the finger veins. In this necessarily small review of the use of biometrics in personal identification, we can also highlight the possibilities of fiducial points of the electrocardiographic signal. This has been studied by Silva *et al.* in [14] where they were able to achieve a 99.97% subject recognition rate.

There are still many other biometric techniques applicable to the identification of a person which are based on his/her dynamic parameters, typically those kinematic ones. In this sense, there are active areas of interest as those which use the human motion analysis to identification of the person, for example, using video recognition [15, 16], integrating sensors on the individual [17, 18, 19] or even on the floor [20].

The IoT gives us the possibility of gather data on the interaction of the individuals with the environment. One of the many final results of the analysis of this huge amount of data can be the identification of the user through the interaction with the environment. And this method could be considered as an indirect biometrics approach able to identify a person through its interaction with the things. In [21] Shao *et al.* present a door access system which uses the effects produced in Bluetooth beacons signals by a person who accesses a door in a way to identify him. The results are promising as they demonstrate that this system is able to identify the user during the door access with a precision up to 69% in a small set of users.

Following this discussion, we would ask ourselves if the way a person interacts with a door can be used to identify him/her. In our best effort, we have only found two works on this subject. In a preliminary paper, [22], Fujinami *et al.* combined accelerometers attached to the door and to the wrist of the user to identify the person opening the door. In a deeper research, [23], Piltaver *et al.* describe an approach for recognising a person entering a room only by using the door acceleration obtaining an accuracy of 90%, confirming their hypothesis. In these two cases, the identification of the person is done once the person has already entered the room, hence these approaches are unsuitable to be used in an access control system. As we are interested in a method useful to identify a person prior to granting him/her access through the door, we must focus on the interaction with the door handle. In other words, to accomplish the identification while the person is operating the handle to open the door. In this way, we comply with the view of accomplishing intelligence in an IoT environment.

The experimental results show us that the interaction with the door handle includes enough information to identify the person who is trying to open a closed door suitable to be used in an access control system.

The paper is organised as follows. In the next section, we present the background of the study, with a description of the state of the art of the related technologies. In Section 3 our approach to studying the subject is described together with the experimental setting and how the experiments were done including the description of the acquisition platform, the data set obtained, and feature extraction. In Section 4 our results on the application of several classifiers over six suites of features are presented and in the Section 5 the main findings are highlighted and the future work outlined.

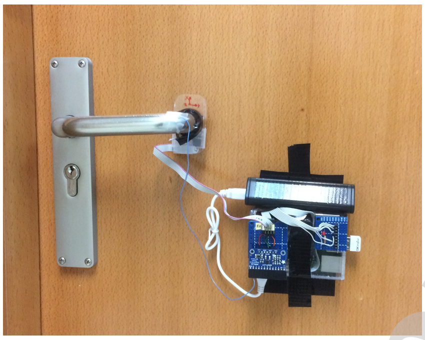

Figure 1: Deploying of the acquisition platform.

Finally, a set of conclusions will be found in Section 6.

3. Materials and Methods

This section describes the procedures and approximations made to obtain a suitable data set an also a convenient feature space in order to validate our main hypothesis throughout the use of a sort of common classifiers. The acquisition platform used to acquire our data set will be described in terms of its hardware and software components and then we will account for the application of the Dynamic Time Warping technique to segment the data set time-series and feature extraction.

3.1. Acquisition Platform

Any platform suitable to be used to collect data sets in AmI area must comply, in addition to the usual IoT sensoring requirements, a set of properties that gives credibility to the experimental setting. Hence, the hardware platform must be unobtrusive and look and feel transparent enough for the subjects of our experiment. We have built a straightforward hardware platform consisting of a small MEMS module attached to a common lever door

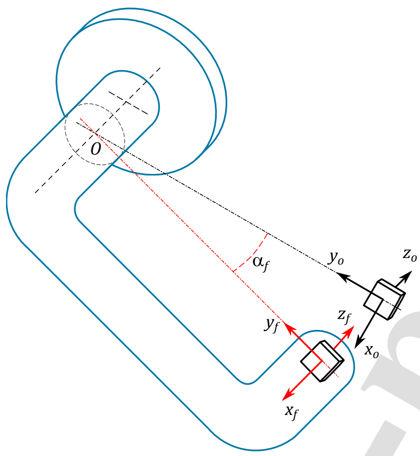

Figure 2: Outline of the lever door handle used in the experiment. The plate affixed to the end of the lever stands for the sensor breakout. The sensor basis $(\vec{x}, \vec{y}, \vec{z})$ moves jointly with the lever between the two stop positions: *initial rest* position 0 and *end stop* final position f; θ_f is the maximum angular displacement (about 30^o) that is expected to be reached in every intent to open the door. The lever rests horizontally at the rest position and $\vec{x}_0$ is supposed to point downwards; $\vec{z}$ must be always perfectly aligned with the rotation axis of the door handle and $\vec{x}$ and $\vec{y}$ move in a plane perpendicular to the rotation axis of the mechanism.

handle controlled by a small computer affixed to the door (see Figure 1). Althouhg there is other alternative proposals related with the idenfication of objects by meant of the touch [24] we have chosen the use of a MEMS module comprising and accelerometer and a gyroscope in order to make a transparent and unobtrusive identification. This device collects information of a 6-DOF sensor and makes the data available through a wireless network. We consider the inertia added to the physical setting almost negligible.

Figure 2 depicts the geometry statement of the sensoring platform and the door handle. The mechanism sits at 1.05 m (3.4 ft) from the floor and the lever length is 0.13 m (5 in). According to the sensor positioning, we can

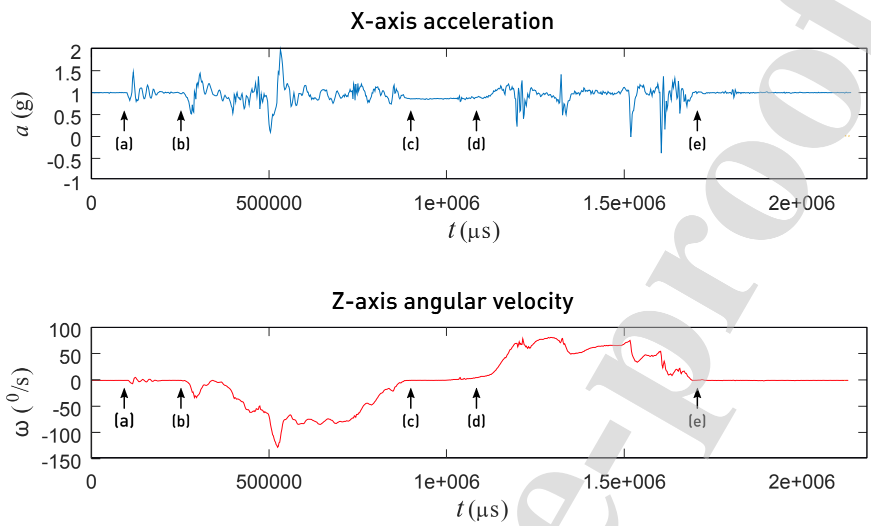

Figure 3: Plots for the x-axis accelerometer and the z-axis gyroscope values for actual acquired data. A rough inspection of both curves allows us to match approximately each piece of them with a different stage of the user interaction: (a) the hand of the subject gets in contact with the lever, (b) the subject starts to push down the lever, (c) the lock mechanism meets the stop end, (d) the subject starts to release the pressure on the lever and (e) the lever returns to its initial rest state.

conclude that the outcome values coming from the sensors for acceleration, $\vec{a}$, and angular velocity, $\vec{\omega}$, must comply certain properties derived from the position and the holonomic constraints of the mechanism. In the initial rest position $\vec{a}_0$ must be very close to $(g, 0, 0)$ and at any other instant $\vec{a}(t)$ will be approximately $(g \cos\theta(t), g \sin\theta(t), 0)$ being $\theta(t)$ the angular displacement of the lever.

If we neglect the possible mechanical looseness of the door handle and assume that the system is perfectly aligned, the ω_x and ω_y components became 0 and then $\vec{\omega}(t) = (0, 0, \omega_z(t))$. In fact, considering that the vector basis for the sensor systems rotates jointly with the door handle we can consider that $\dot{\omega}_z(t) \simeq a_x(t) - g\cos\theta(t)$. Beyond the scientific interest to check the validity of the previous assertion, it is important to notice that the data obtained from the accelerometer is much more spiky and noisier than the numeric derivative $\dot{\omega}_z$. Perhaps a better quality door handle would have noticeably reduced the influence of the spurious mechanical imperfections in the sensor readings.

In the Figure 3 the two essential values (ω_z and a_x) from an actual experiment are plotted. We decided to keep the log of both measurements but in the rest of the paper, it is assumed that only the angular speed is used, because it includes enough information to validate our hypothesis and its lower noise eases the identification process.

The hardware design of our platform is driven by our experience in sensoring and data gathering [18, 19]. The main board consists of a Raspberry Pi/2+ with a Broadcom BCM2837 ARM7 Quad Core Processor running at 900 MHz, and 1 GB of RAM. The sensoring element of our platform is a MPU 9250 (Motion Processing Unit) that can be found in some smartphones. This chip provides a full 9 degree of freedom (DOF) solution with a wide range of sampling rates and a superb bit resolution [25]. The wiring of the sensor board was made throughout a I2C interface with the GPIO pinout offered by the Raspberry; in this way the cable only requires four wires and it is very light and flexible.

Programming was done in Go language on a Jessie Raspbian software platform. Several measurements were made to ensure that the system could cope with the frequency requirements needed in our experiment, and the system verified a sampling frequency no less than 600 Hz. This performance is more than enough for our purposes. In a previous work by Gjoreski *et al.* they fix accelerometers and gyroscopes to a door and get quite promising results with sampling frequencies below 100 Hz [23]. In our case we focus in the handle, and, as it is subject to more brisk actions and forceful movements, we decided to attain sampling frequencies of no less than 500 Hz, so that the quality of the signal would not be compromised, although some further filtering and subsampling will be made from the original data.

3.2. Data Set Acquisition

Our data set consists of series of vectors formed from angular speeds and accelerations, conveniently labeled with time in μseconds. A total of 47 individuals (13 female and 34 male) aged from 18 to 68 years old collaborated in the making of our database. Independently of whether the subject was right- or left-handed, the individuals were asked to interact as naturally as possible with a right-handed door handle for 25 repetitions on a firmly closed door. The subjects were asked to try to open a closed door: (i) to start at a distance of 3 m right in front of the door and walk as they usually will do with the intention of acting on the door handle, then (ii) to act on the door handle, (iii) to wait a very short time with the lever on the end-stop position, (iv) to release the force while handling the door handle, and finally (v) to move away the hand.

For each of the donors, age, gender and height were recorded and stored aside the samples. No other personal information was included on it. All the persons were informed about the purpose of the corpus, and that the recorded data would be made available for the community in an anonymous way, and they signed an uninterested agreement donating of the data.

The first 200 samples of each series capture the rest state of the system before the instant in which the platform detects a significant change in the energy of the signal; from this very moment the platform acquires a fixed

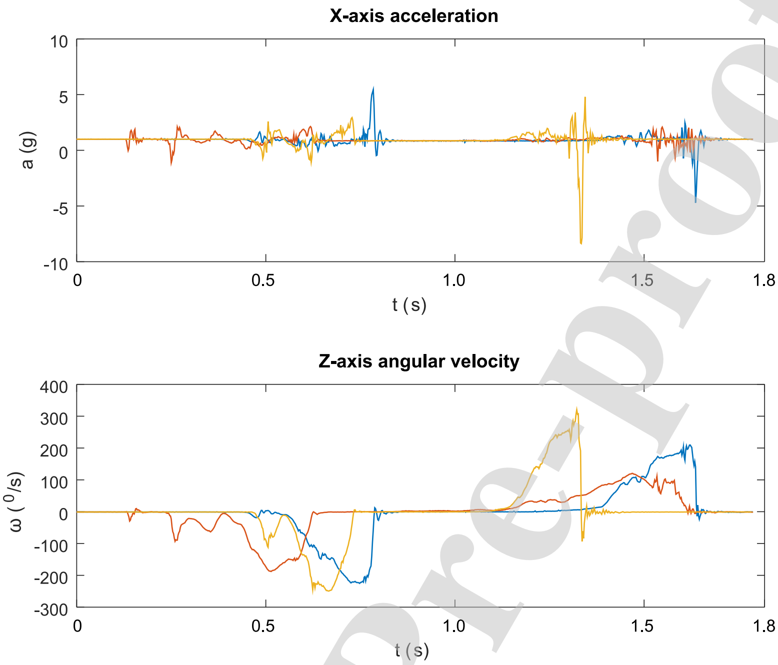

Figure 4: Acceleration (a_x) and angular velocity (ω_z) data acquired from three different study subjects interacting with the door handle following given instructions.

amount of samples up to complete a total duration of 2.5 s, that we considered large enough to gather all data. Discarding some series that did not contain the whole user interaction with the door handle was a minor problem, and finally a corpus consisting of 20 repetitions for each subject was created and labeled, resulting of a total of 960 attempts of opening a door.

Figure 4 shows the samples of three different subjects from our study. These time series serve to illustrate the usual acceleration and angular velocity curves acquired according to the protocol of our study.

Each sample in a time series is timestamped in μs, the value of acceleration for every axis in floating point of g units with a precision of 6 digits and the value of angular speed in floating point in the range $[-250\ ^{\circ}/s, +250\ ^{\circ}/s]$ with a precision of 4 digits. As can be seen from the plot of the angular speed in the Figure 3, for a data series it seems feasible to perform a (i) *segmentation* of the signal in order label each portion of the series and then (ii) apply some kind of feature extraction technique for some *pattern recognition* mechanism.

3.3. Application of DTW to Time Indexing for Segmentation and Feature Extraction

A very usual approximation to deal with compounded n-dimensional series is to apply some kind of segmentation technique that could break the task of recognition into a series of easiest tasks in a time pice-wise manner. There are many suitable algorithms with applications to biomedical signals, image, speech recognition and big data [26]. In our case, the nature of our problem makes the top-down global approximations very useful to this task. A good candidate for partitioning the signal is to apply Dynamic Time Warping techniques (DTW) matching the data series against a synthetic pattern resembling the real data in order to index the borders of the segments we are trying to identify (*rest, press*, *hold*, *release* and *rest*) phases.

This application is not new and Keogh *et al.* present a good review to DTW fundamentals [26] and its applications to time indexing. Malfrère and Dutoit apply DTW to segmentation and synthetic speech in [27], and Müller deals with its application to Information Retrieval and Data Mining [28]. In short, DTW works fine under the assumption that two time series of data (X, W) present the same, or a similar, shape except for a deformation in their time axes (t, τ). One outcome of a DTW process is warping map, R_{XW}, that relates pairs of values from t and τ, $r_i = (t_i, \tau_i)$ where $1 <= i <= I$ and

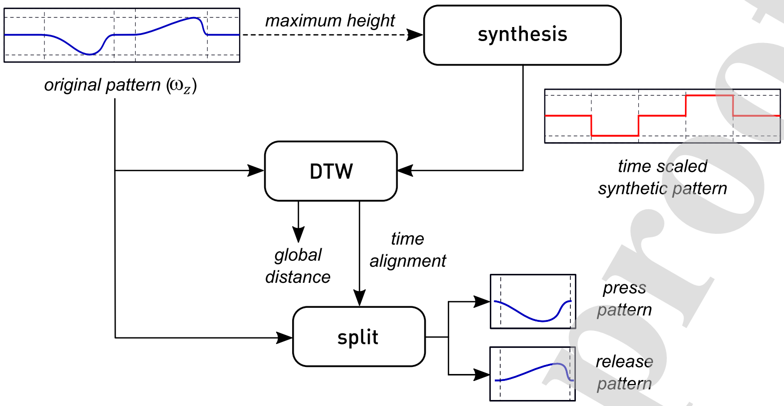

Figure 5: Flowchart of the border detection stage. The process comprises a preliminary computation of the maximum peak from the entire angular velocity data. A synthetic series with two *windows* is computed and then a DTW time aligning is performed. The vector relates the two temporal axes and is used to index the input data times matching the windows.

I is the number of pairs of R, preserving certain continuity and derivative properties as stated in [26]. In addition, the DTW procedure will also provide a global distance value, D, that can be considered as a dissimilarity measure of the two curves.

This technique requires the user to specify two important items: first, the procedure would need to compute the distance between any two points of the series for which a local distance function must be given; second, some statement about what is an admissible local time deformation, for example, to maintain time causality and derivative properties. In our case, we have chosen the maximum and minimum derivative of R_{XW} as $(3, 1/3)$. We will use R_{XW} to *locate* events of the measured signal $X(t)$ from specific $W(\tau)$ points.

In a practical matter, we propose to compute a time alignment function

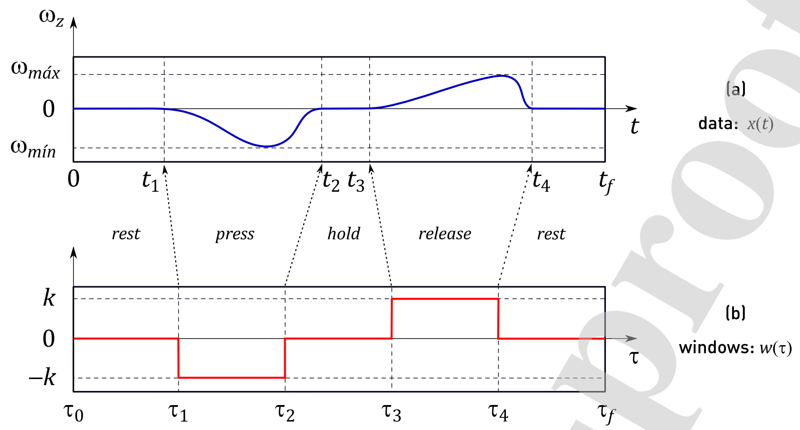

Figure 6: Two sequences X and W suitable to be used in a DTW procedure. The plot (a) represents the angular speed of the z-axis of our experiment and the plot (b) the proposed candidate time series with two windows that resemble the first plot. The arrows between the plots depict the synchronization effort made by the DTW procedure, trying to align both time scales. The values $\{\tau_i\}$ are computed as the average values observed aligning one set of randomly chosen angular speed series from each user and an initial estimation. The values fixed for the rest of the work are $\tau_1 = 397$ ms, $\tau_2 = 760$ ms, $\tau_3 = 1153$ ms and $\tau_4 = 1498$ ms.

between windowing series and the original time series. From this function it could be easily derived the limits of the press and release patterns contained in the original data, such as is depicted in Figure 5.

To segment our data series we have proposed a simple and rough synthetic pattern as the one depicted in Figure 6.(b) where k is computed as the half value of the maximum absolute value of the source signal with data (X) like the one in Figure 6.(a). For our data set, this synthetic pattern gives quite good results, and it is not our goal presently to fine-tune the system at this stage to validate our main hypothesis. Even more, to alleviate the computational load on the system, subsampling is a quite valid option if the following feature extraction stage is robust enough. In our case, as the algorithm used for feature extraction relaxes the conditions at the beginning and at the end of the pattern, this subsampling would not affect the outcome substantially. As a result of this stage, the collection of obtained time estimates will be used to compute fragment durations and therefore to serve as input values for the classifying stage.

3.3.1. Application to Feature Extraction

Most of existing machine learning algorithms are designed to receive as input a fixed set of values intended to summarise the relevant information of a specific pattern concerning to a classifier. In this stage, our time series comprising angular speed is going to be condensed in a set of values, *feature vector*, intended to contain the valuable information regarding the shape of the time series. Usually, a feature selection is necessary to discard unnecessary values that could mask computationally the important ones for the classification stage. In spite of the feature selection being a difficult matter concerning statistics and computing science, several developed data mining tools automate up to a certain point this task.

For this stage, we have decided to implement a rather straightforward feature extraction method that allows us to compute the parameters that intend to describe the shape of the angular speed for both 'press' and 'release' actions (Figure 7). A set of 11 different synthetic waveforms coding a wide sort of shapes (*square box*, *triangle*, three different *jigsaw* functions and five different *trapecium*) were compared to all the patterns of our data set using a DTW procedure. The parametrisation of the DTW method comprised (3, 1/3) derivative restrictions on the warping function and also the boundary conditions of the search algorithm were relaxed to take into account errors

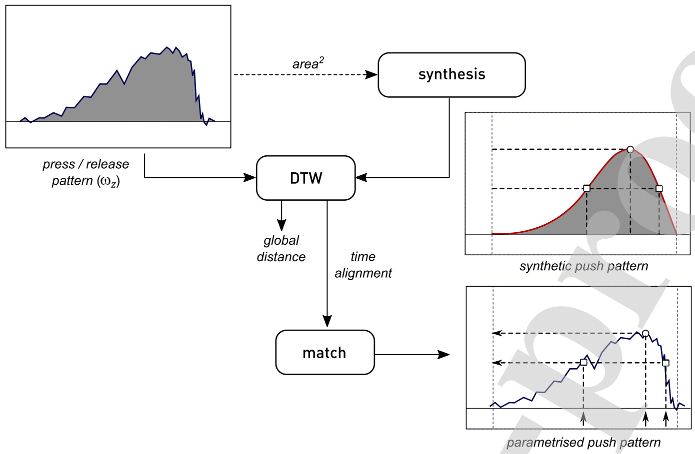

Figure 7: Flowchart of the feature extraction stage. The process comprises a preliminary computation of the area under the curve that serves as normalization parameter to synthesize our proposed fitting curve for ω_Z. The a DTW time aligning is performed. The procedure produces two useful outcomes: a global distance result, and an intended time aligment relation for the series. This data permits us to relate specific points from the synthetic curve with original input data.

in the segmentation stage. Finally, one of the former waveforms was selected complying with having the best average global distance. The election of the local restriction, 3, 1/3 (P1 according to [26]), is a usual one and serves well for most uses in pattern recognition according to our previous experience.

The plot in the Figure 8 shows the shape of the selected function used to be compared against every pattern using the DTW procedure. This function is a refined version of the most frequent waveform (a slanted triangle function) computed as above. A new synthetic pattern will be computed each time a feature extraction is needed, with the same duration and area that the sampled data, as is shown in Figure 7.

This method permits to pinpoint some specific locations on the original

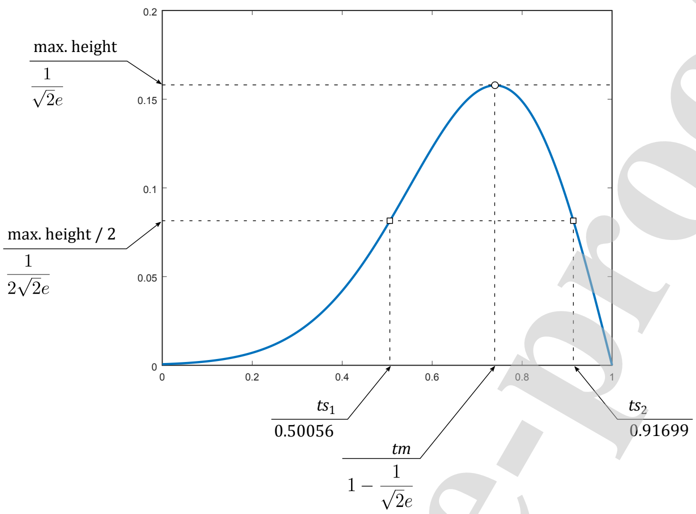

Figure 8: Plot of the function f used as a basis for the synthetic pattern to be compared with the angular speed signal. Below each line tagging the height and the half-height are the exact values for t and $f(t) = A(t-1)\exp -(e(t-1))^2$. This function intersects the horizontal axis at $t = 1$ and the area under the curve, $\int_0^1 f(t)$ ($\simeq 0.06766$), permits to generate a synthetic pattern that equals the area of the experimental series ($\omega_z(t)$).

signal in an elegant and precise form, assuming that it resembles this exemplary pattern. In case the signal contour does not resemble the proposed pattern, the extracted points of interest will not be very accurate approximations, but in any case, the DTW algorithm will provide a global distance that could also serve as a feature of the pattern.

As a result of this stage a set of measures are available that could be used as feature candidates: (TM) the time from the beginning of the curve when the maximum value of angular speed inside the pattern occurs; (L) the duration of the press or release action; (A) the area of the curve; (A2) the rotational energy calculated through the integration of the squared angular speed; (TS1) the time when the curve reaches up to the middle of the maximum height; (TS2) the time when the curve falls up to the middle of the maximum height; (D) the global distance provided by DTW.

All these features are provided separately for the press and release phases. To distinguish between them, a 'P' or 'R' will be appended to the names given above. Also, an additional set of features has been computed subtracting each feature value of the release phase from the corresponding feature of the press phase. In this case, the features are labeled with an additional 'S'. All of these items must be considered as a proposal for a subsequent feature selection consideration.

4. Results

To answer the key question about the utility of data obtained in the movement of the door handle to identify the person who is trying to open a door, we have chosen six different combinations of features, or suites of features, to feed several different classification approaches. The details on each one of these suites can be found in Table 4.

The feature suites *Press* and *Release* correspond to the features of press and release movement of the door handle, respectively, while the features on the *Substr* suite are calculated subtracting the value of the features in the press and the release phases. The suite *PressRelease* is composed by the union of the features of *Press* and *Release*, which accounts for the assumption that to identify an individual both sets of features must be considered jointly. While it is not usually a good decision to take all the features in an indiscriminate way, we also considered the suite *PressReleaseSubstr* to compare the classification results with the former one.

Decision tree classifiers perform feature selection as part of their overall

Feature Suite	Features
Press	{L-P, A-P, A2-P, D-P, TM-P, TS1-P, TS2-P}
Release	{L-R, A-R, A2-R, D-R, TM-R, TS1-R, TS2-R}
Substr	{L-S, A-S, A2-S, D-S, TM-S, TS1-S, TS2-S}
PressRelease	*Press* ∪ *Release*
PressReleaseSubstr	*Press* ∪ *Release* ∪ *Substr*
FourLevels	{A2-P, A2-R, D-P, L-R, D-R, A-R, A-P, A-D}

Table 1: Feature suites considered in the classification.

operation [29]. From the result of this classifier we decided to include an *a posteriori* additional feature suite, considering the features in the 4 top levels in a decision tree classifier to compose the last suite, called *FourLevels*.

We have made a choice of the most popular classifiers found in the literature arising from different classifiers families to test our hypothesis [30, 31], as each of the classification methods shows different efficacy and accuracy based on the kind of data sets [32].

The chosen classifiers are: k-Nearest Neighbor (k-NN), Support Vector Machines (SVM), Naive Bayes (NB), Decision Tree (DT), Random Forest (RT), Artificial Neural Network (ANN), and Logistic Regression (LR).

Each one of the classifiers has been evaluated with our data set assuming the best default values stated by the Orange toolkit [33] (Ver. 3.11.0) performing a 10-fold cross-validation. The results have been interpreted in the

	Press	*Release*	*Substr*	*Press-Release*	*Press-Release-Substr*	*Four-Levels*	μ	σ
k-NN	0.618	0.610	0.578	0.689	0.676	0.689	0.643	0.043
SVM	0.858	0.829	0.800	0.898	0.897	**0.907**	0.865	0.040
NB	0.819	0.792	0.738	0.873	0.871	0.877	0.828	0.051
DT	0.600	0.587	0.567	0.618	0.625	0.615	0.602	0.020
RF	0.736	0.726	0.698	0.817	0.809	0.832	0.770	0.051
ANN	0.859	0.830	0.810	**0.904**	0.900	**0.912**	0.869	0.039
LR	0.836	0.805	0.778	0.890	0.890	0.889	0.848	0.045
μ	0.761	0.740	0.710	0.813	0.810	0.817		
σ	0.104	0.095	0.094	0.106	0.106	0.109		

Table 2: Values of AUC of the different classifiers with the six different features suites. Average (μ) and standard deviation (σ) has been added for each classifier and suite.

sense of *area under the curve* metric, AUC. As stated in [34, 35], AUC is a good "single number" evaluation measure over accuracy when evaluating and comparing classifiers. This metric estimates the probability that a randomly selected positive case will receive a higher score than a randomly selected case [36]. Terms such as "excellent", "good" and so on, will be used to qualify the identification with the same meaning as proposed by Tape in [37].

Table 4 shows the AUC values for the classifiers considering the different groups of features in the data sets showed in Table 4. Some remarkable values have been emphasised and will be discussed in the following section.

5. Discussion

As we might expect, the values of the outcomes of AUC for the different classifiers shown in the Table 4 are quite different, depending on the feature suite considered. First, we study the influence of the features suite choice in the overall classification rate. Therefore, the average AUC value for all the classifiers is computed and provided in the table of results. Following, we focus on the analysis of the performance of the classification itself, in search of the method which performs better. Once more, the average of the AUC for each of the classifiers is calculated taking into account all the feature suites. Finally, we will focus on the analysis of the best identification results we have found.

As can be seen in the table of values of AUC, the feature suite *PressRelease* seems more promising (0.813) that the *Press* and *Release* considered individually ($0,761$ and 0.740). Then we conclude that although the information obtained from the *Press* feature set and the *Release* set could be used individually to try to identify the subject, it is better to merge both feature sets.

To merge the pattern shapes in the press and release phases, as we did in the *Substr* suite, does not seems to be useful, because it gets the lower score, globally and for each one of the classifiers. Even more, when combined with the *Press* and *Release* suites, it does not perform better than the *PressRelease* alone.

We found that *FoulLevels* gives results as good (0.817) as *PressRelease* (0.813) and *PressReleaseSubstr* (0.810). Although the difference is not relevant, the suite *FourLevels* has a significantly less amount of features, 8 vs. 21, what is an indubitable computational benefit as in the feature extraction process, as in the classification task. This could be of interest for anyone working in building a real-time identification system.

After analysing the results shown in Table 4 searching for the performance of each classification method, we can conclude that the neural network approximation seems to be the more promising one. The global performance of the Artificial Neural Network (ANN), μ, is the best (0.869), closely followed by the Supported Vector Machines (SVM) method (0.865). In contrast, k-Nearest Neighbor (k-NN) and Decision Tree (DT) classifiers show "poor" results globally and also for each one of the feature suites.

The best classification result is obtained when the Artificial Neural Network (ANN) is applied to the feature suite *FourLevels* (0.912). Its performance can be graded as "excellent". The same could be said of the Support Vector Machines (SVM) classifier when applied also to the *FourLevels* suite (0.907), and of the Artificial Neural Network (ANN) working on the suite *PressRelease* (0.904).

Unfortunately, we can not compare our results with those we found in the review of the bibliography. Neither the metrics used nor the data sets involved in the experiments allow making that because they are different. Therefore, the conclusions that we could obtain would not be meaningful.

The best results in the classification of Artificial Neural Network and Support Vector Machines may be due to the sample sizes and types of the variables considered in the different features suites considered, as is reported in [38].

Regarding practical matters about the implementation of this method, some considerations about space and time costs must be done. Time and space requirements of the tasks previous to the identification stage can be considered constant because they are related mainly to the sampling frequency and DTW resolution. On the other hand, the identification stage cost would depend mainly on the type of the employed algorithm, both in the temporal and storage domain. Therefore, the scalability of any proposal based on this methodology will depend on these considerations.

The results from our evaluation demonstrate that the main hypothesis of this work is valid. In other words, the way a user handles a door handle can be used to identify him/her, making it useful for an access control task.

5.1. Future Work

A future research work in this area, must take into account additional synthetic curves and improve the feature extraction and selection in order to obtain a more reliable authentication system based on the act of using a door handle.

Also, a characterization of types of users and it's modes of interact with a door handle is needed, doing a deeper study about the biomechanics in relation to different kinds of door handles. Although the characteristics of a knob could be very close to those of a handle, as the opening actions implies a rotation around an axe in both cases, specific experimental work must be done for each type of knob or handler to study its physical behaviour and the feasibility of the method.

Although the scenario in which this experiment has been done is well defined, it leaves some open question regarding the identificación the user in different behavior contexts, as "running into the door", or involving some other activities while is opening the door, as "speaking with a mobile phone" for example. Our intuition is that it would be possible to identify users in different behaviour context similar to those enumerated above, but new data acquisition in several settings is needed to be done in order to address this.

From a practical implementation point of view, further considerations about real-time feasibility must be addressed: defining a suitable algorithm to be embedded in a real system able to identify the person trying to open a door in real time conditions.

6. Conclusion

In this work, sensoring capabilities have been embedded in a common door handle in a transparent and unobtrusive way in order to acquire a relevant amount of data about the act of a person interacting with the handle trying to open a door. This could be employed to integrate a common door as an element of an ecosystem of IoT.

For this purpose, a hardware and software system has been developed, and it has been used to gather a data set with information of 47 individuals through 20 repetitions that have been used in a pattern classification task.

Time segmentation and feature extraction were made using time alignment methods and a set of 21 features have been obtained. From this set of features, a selection has been done producing up to six feature suites that have been fed to different pattern classification methods.

Results show that this method could be used to identify the user trying to open a door. Although other traditional methods of identification discussed at the beginning of this article, as for example the token based, are less influenced by the architecture of the physical system, be it a knob or a bar, however we think that the opening by a token may be easier to supplant the identity of the person, through theft, while the setting of the opening movement itself is much more complicated. In multi-factor identification scenarios security is better guaranteed by the combination of different methods. In this case, our contribution could be one of the identification factors, combined with the token, for example. Therefore, our proposal would be applicable in identity verification systems based on several factors. This has several applications for the implementation of access control methods suitable to be integrated into door locks, as an example of the combination of AI and IoT in an unobtrusive and transparent way.

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Highlights

The main hypothesis is that the way in what a user interacts unobtrusively with a door handle is suitable to be used in an identification task.

Sensoring capabilities have been embedded in a common door handle in a transparent and unobtrusive way in order to acquire a relevant amount of data about the act of a person interacting with the handle trying to open a door.

Hardware and software system have been developed, and it has been used to gather a dataset with information of 47 individuals through 20 repetitions that have been used in a pattern classification task.

Results show that this method could be used to identify the user trying to open a door.

Conflict of Interest

This work has been done in the Pervasive Computation Research Laboratory (PERCOMP Lab) at the University of Valladolid. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

No conflict of interest have been identified.