Person Identification using Door Accelerations

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Abstract. This paper describes a novel system for identification of a person entering a room using only the door acceleration data. The main hypothesis is that each user has a unique way of opening and closing the door, and that the differences are sufficient to enable accurate identification of a limited set of people. In particular, two approaches are proposed: (i) identification using machine learning (ML) and (ii) identification using dynamic time warping (DTW). The ML approach first extracts 266 features based on domain knowledge, then performs feature selection to reduce the feature set, and finally performs classification to identify the person. The DTW approach applies dynamic time warping on the raw acceleration signal and identifies the person by finding the most similar signals in the training dataset. The two approaches were evaluated on a dataset of 1007 entrances recorded by 12 people. The results showed that DTW performs best, achieving 86.3% identification accuracy. Even though the accuracy is not high enough for secure access-control applications, the results of the novel approach are promising for applications with a limited number of users. Moreover, the approach is completely unobtrusive to the user — no additional action such as scanning a fingerprint is required — thus it can be used as an assistive technology or for smart-home personalization in offices and homes.

Keywords. Unobtrusive person identification, machine learning, feature extraction, dynamic time warping.

1. Introduction

Person identification is a process that recognizes a person, i.e. establishes that the person being identified is indeed that particular person. Among others, identification is a key prerequisite for personalization of smart house automation – smart home needs to recognize a person in order to adapt ambient parameters according to ones preferences.

This paper deals with automatic identification performed by unobtrusive devices. A disadvantage of existing identification methods (e.g., fingerprint, RFID, PIN) is that the identified person needs to perform an action (enter a password, perform a fingerprint scan) or carry an identification token (key or identification card). In contrast, our approach identifies the person entering a room based on the acceleration produced by the door movement. The main research hypotheses investigated in this paper are whether each user has a unique way of entering and whether the proposed methods enable accurate identification. In the experiments, identification is performed using the acceleration signal recorded by an accelerometer fixed on the door by two methods:

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machine learning (ML) based on extracted features and dynamic time-warping (DTW) of the raw acceleration signal. The goal of the system is not to substitute other reliable identification systems (e.g., fingerprint scanners), but to be used as an assistive technology (assist in daily tasks) and enable smart-home personalization in applications with a limited number of people (e.g., in a home or an office) by making the identification more comfortable, i.e. not requiring users to perform additional action. A reasonable decrease in identification accuracy is tolerated in return for the increase in comfort of identification procedure.

The motivation for the work comes from the commonly observed phenomena that humans can recognize their friends and family members by their voice, silhouette, or even gait and other characteristic behavior. Furthermore, there are several known methods for person identification based on gait [1] and appearance [2] – both with considerable application limitations. Furthermore, body-worn accelerometers have been successfully applied to detect falls [3], recognize person activity [4, 5], and estimate energy expenditure [6], while accelerometers attached to door are used to recognize door malfunctions [7].

1.1. Physics Background and Acceleration Signal Description

Several phases of door movement can be observed as the person enters (as shown in Figure 2 and Figure 3). The door is motionless before the entry, therefore minor deviations from the static values of accelerations in each direction is caused only by sensor noise and vibrations due to outside influences. When entering, the person first accelerates the door in order to open it, which is observed as an increase in angle of the door, angular velocity and acceleration. Then, the acceleration starts to decrease and becomes negative until the door stops at the maximum angle. The door can remain in this state for a period of time or just an instance. Then the person accelerates the door in the opposite direction (closing), angular velocity becomes negative and the angle starts to decrease. Before the door angle returns to zero (door closed) the person decreases the angular velocity. If the door is not slowed down enough (door is slammed), a period of damped oscillation lasting up to about a second is observed after closing the door. Examples are shown in Figure 2 and Figure 3.

The described physical phenomena can be measured using various sensors such as accelerometer, gyroscope, magnetometer, and door-opening angle sensor. The accelerometer was chosen for the experiment because of availability, installation simplicity, past experiences, successful applications, and extensive related work. A 3-axis accelerometer was attached to the door so that one of its axis was aligned with the direction of gravitation, resulting in measurement of gravitation acceleration a_g. The second axis was parallel and the third perpendicular to the door-plane, resulting in measurements of the radial a_r and tangential accelerations a_t respectfully. The gravitation acceleration depends only on the geographical position of the door and remains constant during the entry unless the axis become misaligned with direction of gravity, e.g., when the door is slammed hard and starts oscillating. Radial acceleration $a_r = \omega^2 R$ depends on the angular velocity ω and the distance of the accelerometer from the axis of door rotation R. Tangential acceleration $a_t = \alpha R$ depends on the angular acceleration α and R (Figure 3).

2. Related Work

There are various approaches to identify a person entering a room, home, or building. The person is usually recognized or authenticated using a sensor placed near the entrance, which may be: a fingerprint scanner, a camera-based face recognition, a radio frequency identification (RFID) reader, a PIN pad, or similar. The following paragraphs describe these approaches and explain how they compare to ours.

Fingerprint scanners are one of the most commonly used and well-established identification sensors [8]. With the recent developments in sensor technology, fingerprint scanners are also being used in the high-end smartphones for various security related functions, such as unlocking the phone and authenticating financial transactions [9]. The scanner analyses the person's fingerprint, i.e. the pattern of the ridges and furrows on the surface of the fingerprint, to identify the person. The reason for the success of fingerprint scanners is that each individual has a unique fingerprint, which enables high identification accuracy. Similarly, hand scanners identify the person using a print of the whole hand instead of a single finger. However, there are several limitations for successful identification with a fingerprint or hand scanner: a complete scan with a reliable quality is needed; moisture, sweat and partial scans significantly impair the identification accuracy; and finally, it is obtrusive for the identified person because one has to make an action in order to be identified: take of a glove, wipe out the finger/hand, put the hand on the scanner.

The recent advancements in machine vision enable camera-based approaches for identification of people [10]. This approach analyzes an image of a person's face in order to perform face recognition by matching it to known face images saved in a database. Even though this approach can perform without bothering the identified person, the cameras are not widely accepted due to the intrusion of the person's privacy. Similarly as fingerprint scanners, camera-based face recognition performs poorly with partial face images, and strongly depends on the environment and the light conditions.

Token-based identification is also commonly used. It became attractive with the development of the RFID and Near-Field Communication (NFC) technology [11]. Typically, each user is issued the respective token — for example, an RFID card — that contains data indicating the user's identity. This approach is practical for multi-site large-scale installations of access-control systems having many access points and users. Even though token-based identification is quite effective and commonly used in practice, it is obtrusive because it requires additional effort from the user upon each entry. Furthermore, it is not as secure as the approaches discussed above, because the user may lose the identification token and any other person having the token can access the facility. A solution to this problem is the use of Personal identification number (PIN) instead of a card. However, this approach is still considered obtrusive. First, the person has to remember the PIN, which is problematic because users have to remember multiple PINs (credit cards, web-passwords). Second, it has the same drawback as the fingerprint scanner: it requires an additional effort from the user to enter the PIN. Third, it can be stolen.

The main advantage of our approach is that we use a simple, small and inexpensive accelerometer sensor attached to the door. Therefore, the sensing is completely unobtrusive. To the best of our knowledge, this is the first attempt to identify a person using door accelerations.

3. Identification – Machine Learning

This section presents the classical machine learning (ML) approach with domain-specific features. The approach is shown in Figure 1: the raw acceleration data is first used to extract various domain-specific features, then the most relevant features are identified, and finally the person is identified by a classification model trained using a ML algorithm.

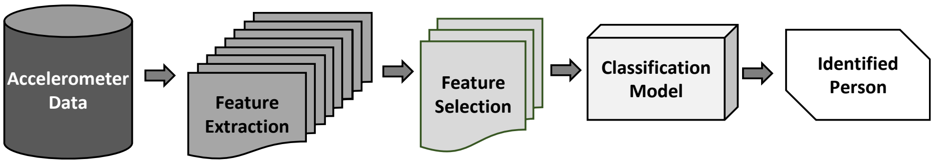

Figure 1. ML approach for person identification using the acceleration signal produced by a door movement.

3.1. Feature Extraction

The identification starts with the feature extraction from the acceleration signal. The method analyzes the acceleration signal for each opening and closing of the door, i.e. the start is when the door starts opening and the end is when the door is closed. First, two additional signal components are calculated: the angular velocity ω and the angle by which the door is opened φ. They are calculated from the radial acceleration a_r as follows:

$$R\omega(t) = \sum_{k=0}^{t} a_r(k)T \quad (1)$$

$$R\varphi(t) = \sum_{k=0}^{t} \omega(k)T \quad (2)$$

where T is the sampling interval. Only the changes in the angular acceleration α, angular velocity ω and the opening angle φ are relevant, therefore the actual values are not needed, hence the constants T and R are irrelevant. In order to calculate the features, the acceleration signal is divided in 14 phases as illustrated in Figure 2.

The interpretation of the phases is as follows:

- 1a–b: the start and end of entrance
- 2a–d: door opens, door stops, door closes
- 3a–f: acceleration changes between negative, zero and positive
- 4a–e: acceleration maximums and minimums in each level-3 subsection

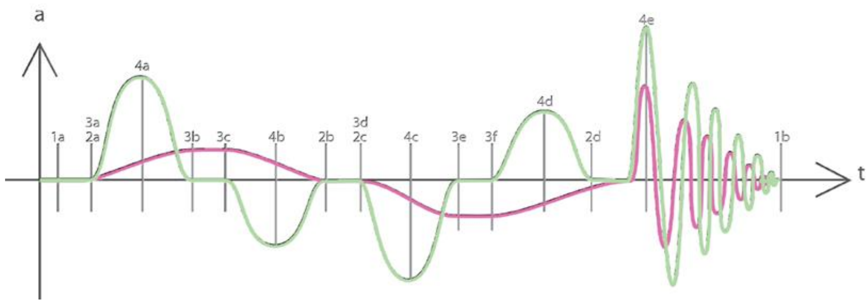

Figure 2. The 14 phases of the acceleration signal. The x axis shows the time (t) and the y axis shows the acceleration α (green) and the velocity ω (red).

Besides the duration of each phase, the following features are extracted for each phase (see Figure 2) and for each parameter (α, ω, φ), resulting in total of 266 features:

- extreme value of the parameter in the particular phase;
- linear interpolation of the slope of the parameter in the particular phase;
- standard deviation of the parameter in the particular phase; and
- area under the curve (integral) of the parameter in the particular phase.

3.2. Feature Selection

The goal of feature selection is to reduce the set of features used for training the classification model. Feature selection reduces the number of redundant (those that provide no more information than the currently selected features) and irrelevant features (those that provide no useful information in any context).

The feature extraction phase presented in Section 3.1 produces 266 features from the acceleration signal. Because door moves with a single degree of freedom, some of these features are redundant (highly correlated) and some are irrelevant. Therefore, the acceleration in the direction that points to the ground is constant (i.e. the Earth's gravity) and irrelevant. Additionally, the accelerations in the other two directions are correlated and the calculated angular velocities and opening angle are derivatives of the appropriate accelerations, which makes them correlated too.

In order to find and remove the irrelevant and the most correlated (redundant) features, a correlation matrix for all of the features was first calculated. We used the correlation matrix which is output from the Principal Components filter in the WEKA toolkit [12]. By analyzing the matrix, the features that are highly correlated (correlation coefficient above 0.75) were removed. The threshold was chosen after empirical analysis of the data. This procedure reduced the number of feature by 169, i.e. from 266 to 97. After removing the most correlated features, the WrapperSubsetEval (WSE) algorithm [13] was applied. WSE was used to further reduce the number of features, so that the learning algorithm can focus its attention to the most relevant features, while ignoring the rest. After applying WSE the final number of features was reduced to 36. The analysis of the 36 features shows that each phase is represented by one or few features. In particular, phase 9, which represents the moment when the user is closing the door (between 4c and 3e in Figure 2) is the most relevant and it is represented by 6 features. Phases 6, 10, 11 and 12 seems to be not so relevant and they are represented by 1 feature. Another important thing to note is that the extreme value for the angular velocity is really important, therefore it is represented with 11 features.

3.3. Classification

Once the features were extracted, analyzed and the most relevant were selected, the feature vector was fed into a classification model. The model is trained to identify the person that enters the room according to the feature vector extracted from the acceleration signal. The person's name is used as the class label (the value to be predicted). Four classification algorithms were considered when constructing the model: Decision Tree j48 [14], Random Forest [15], *k*-NN [16], and Support Vector Machine (SVM) [17]. The results of each algorithm are given in Section 6.1.

4. Identification – Dynamic Time Warping

The second method used to identify people entering through the door was dynamic time warping (DTW) in connection with two variants of the *k*-nearest neighbors method. The following subsection introduces the dynamic time warping algorithm, while its application for identification is described in the subsequent section.

4.1.1. Dynamic Time Warping

Dynamic time warping [18] is a method that was successfully applied in many areas such as speech recognition [19], handwriting recognition [20], gesture recognition [21], time-series clustering [22], etc. The DTW algorithm finds the optimal match between two time series by non-linear stretching of both time series in the time dimension. An example for two door entry acceleration signals is illustrated in Figure 3. The matching is then used to calculate the dissimilarity of the two time series, i.e. the distance between the optimally time-stretched time series. The computed DTW distance is in sequence used to find the most similar time series.

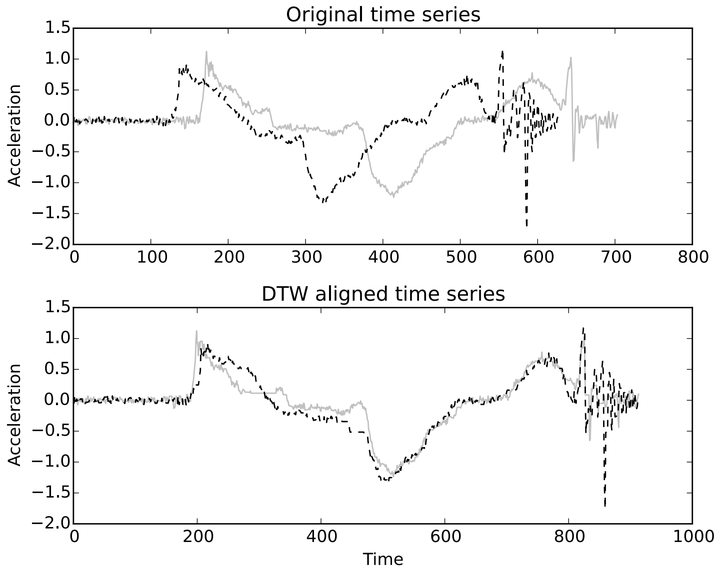

Figure 3. An example of recorded and DTW aligned acceleration during two entries.

DTW algorithm first computes a $n \times m$ distance matrix C representing the pairwise distances $c(x_i, y_j)$ between the points in time series X and Y of lengths n and m respectively. Manhattan, Euclidean or other distance measure can be used. Then, the algorithm computes the DTW distance $D(n, m)$ using dynamic programming algorithm based on Equations 3, 4 and 5.

$$D(1, j) = \sum_{k=1}^{j} c(x_1, y_k),\ j \in [1, m]\ \mathrm{D(1,j)} = \sum_{\mathrm{k=1}}^{\mathrm{j}} \mathrm{c(x_1, y_k), j} \in [1, \mathrm{m}] \tag{3}$$

$$D(i, 1) = \sum_{k=1}^{i} c(x_k, y_1),\ i \in [1, n] \tag{4}$$

$$D(i, j) = min\{D(i-1, j-1), D(i-1, j), D(i, j-1)\} + c(x_i, y_j),$$
$$i \in [2, n], j \in [2, m] \tag{5}$$

Finally, the optimal warping path is found from the accumulated cost matrix D using a greedy algorithm tracking back the lowest cost path from item (n, m) to the item (1,1) — ensuring that the beginnings and ends of the two time series are aligned. In between, the path can either keep the time series unstarched by moving with step (1, 1) or stretch one or the other time series by moving with step (0, 1) or (1, 0).

This naïve DTW algorithm has $O(nm)$ time and space complexity, however there are more efficient algorithms such as FastDTW [23] and SparseDTW [24].

4.2. Identification with Dynamic Time Warping

In order to identify a person that entered the door, the DTW distance between the door-acceleration time-series recorded during the entry and the labeled acceleration time-series of previous entries (labels correspond to persons) is computed. The labels of the most similar previous entries are then used to identify the person who entered the door using one of the two variants of the k-nearest neighbors method.

The first approach is to identify the person entering the door as the most frequent label among the k most similar previous entries — majority voting. If several labels have an equal frequency, a random label among them is predicted as the identity.

The second approach is to use weighted voting. This approach considers the entries that are more similar to the identified entry as more relevant by assigning them higher voting weight compared to the less similar entries. The weight of the vote $w = 1/d$ for each of the k most similar entries is inversely proportional to its DTW distance d from the identified time series. The votes are summed for each label and the predicted identity is the label with the highest sum of votes. Again, if several labels have an equal sum of votes, a random label among them is returned as the predicted identity.

5. Experimental Data

The experimental dataset was recorded in an office. The office door was equipped with a 3-axis accelerometer fixed near the door handle. Total of 12 people (aged 21 to 87) were asked to enter and leave the office multiple times. A total of 1007 entries were recorder. In order to obtain unbiased recordings, the volunteers did not know that the goal was to record the movement of the door. Instead, they were asked to perform the following task: remember a password with a dozen of characters written on a paper in the office and then to re-write the password on a paper outside the office. During the recordings, an experiment supervisor labeled each entry using a smartphone, which was synchronized with the acceleration data. The supervisor marked the start and the end of each recording, and labelled each entry with the person's name.

6. Experimental Results

6.1. Machine Learning

Table 1 shows the results for the ML approach. The results are given for two cases: before feature selection (266 features) and after the feature selection (36 features). The results for each of the four classification algorithms are presented: Decision Tree j48, Random Forest, *k*-NN, and Support Vector Machine. The difference in accuracy was compared using paired T-test with *p*-value of 0.05.

Table 1. The classification performance (recall value for each person and the overall accuracy) achieved before the feature selection (266 features) and after the feature selection (36 features) for the four classification algorithms: Decision Tree j48, Random Forest, *k*-NN, and Support Vector Machine.

		Before feature selection (266 feature)				After feature selection (36 feature)			
	ID	KNN	SVM	Random Forest	j48	KNN	SVM	Random Forest	j48
Recall	0	96.4%	96.4%	96.4%	90.4%	96.4%	97.6%	94.0%	86.7%
	1	98.0%	98.0%	98.0%	98.0%	98.0%	98.0%	100.0%	98.0%
	2	87.8%	91.8%	93.9%	55.1%	83.7%	79.6%	87.8%	63.3%
	3	68.8%	72.9%	77.1%	62.5%	77.1%	60.4%	70.8%	64.6%
	4	70.3%	69.3%	72.3%	60.4%	76.2%	70.3%	75.2%	53.5%
	5	68.6%	76.2%	75.2%	61.0%	67.6%	77.1%	68.6%	57.1%
	6	58.5%	78.7%	78.7%	58.5%	72.3%	79.8%	74.5%	66.0%
	7	76.9%	82.1%	69.2%	66.7%	74.4%	46.2%	59.0%	56.4%
	8	64.8%	74.6%	70.4%	66.2%	74.6%	71.8%	73.2%	64.8%
	9	98.6%	97.6%	96.2%	94.7%	98.6%	98.1%	97.6%	91.9%
	10	54.9%	66.7%	60.8%	86.3%	64.7%	56.9%	66.7%	74.5%
	11	85.7%	92.4%	85.7%	82.9%	92.4%	97.1%	88.6%	76.2%
	Accuracy	79.9%	84.9%	83.3%	75.9%	83.7%	82.6%	82.5%	73.3%

The results show that in general the overall accuracy is either increased (for the *k*-NN method) or stays the same (the noted decrease is not statistically significant) as the number of features decreases from 266 to 36. This confirms the advantage of using the feature selection method to remove the irrelevant and redundant features. The significant increase in accuracy from 79.9% to 83.7% for the *k*-NN method is mainly because it does not have a mechanism for dealing with redundant and irrelevant features (it uses all of the features when calculating the distance between two instances), as opposed to the other three methods.

Table 2. The confusion matrix for the *k*-NN algorithm — the best performing one with the selected feature set. Recall and precision are given for each person as well as overall identification accuracy.

		Predicted Class (Person)												
True Class (Person)	ID	0	1	2	3	4	5	6	7	8	9	10	11	Recall
	0	80	0	0	0	0	1	0	0	0	2	0	0	96.4%
	1	0	49	0	0	0	0	1	0	0	0	0	0	98.0%
	2	1	0	41	2	0	0	1	0	1	3	0	0	83.7%
	3	0	0	3	37	0	2	4	0	0	1	1	0	77.1%
	4	0	0	1	1	77	12	6	2	0	2	0	0	76.2%
	5	3	2	4	1	13	71	5	4	0	2	0	0	67.6%
	6	0	1	3	5	1	2	68	0	10	2	0	2	72.3%
	7	1	0	1	0	1	7	0	29	0	0	0	0	74.4%
	8	0	0	0	1	5	4	7	1	53	0	0	0	74.6%
	9	1	0	1	0	1	0	0	0	0	206	0	0	98.6%
	10	0	0	0	0	0	0	0	0	0	0	33	18	64.7%
	11	0	0	0	0	0	1	0	0	0	1	6	97	92.4%
Precision		93.0%	94.2%	75.9%	78.7%	78.6%	71.0%	73.9%	80.6%	82.8%	94.1%	82.5%	82.9%	Accuracy: 83.7%

Table 2 shows the confusion matrix for the *k*-NN algorithm (using the selected features set), which was the best performing one achieving 83.7% accuracy. It also lists the recall and precision values for each person. The confusion matrix shows that person 10 has the lowest recall (64.7%) and is often incorrectly identified as person 11. Similarly person pairs 4-5 and 6-8 have similar entries and are mutually misidentified.

These results show that there is a considerable difference in identification accuracy for different people and that some people have similar ways of opening and closing the door, which in some cases makes the identification difficult. Therefore, the system is not appropriate to identify large number of users, since it is not able to distinguish similar entries of different people well.

6.2. Dynamic Time Warping

The identification accuracy of the two approaches using DTW for various number of nearest neighbors is shown in Figure 4. The identification accuracy of majority voting approach was computed using 1 to 10 most similar entries. Using the single most similar entry results in 84.81% identification accuracy. The highest accuracy of 85.53% was obtained with 7 most similar entries; however, one-tailed Z-test with *p*-value 0.05 shows that the improvement is not statistically significant. In fact, the only statistically significant difference is the decrease of accuracy from one to two nearest neighbor which yields the lowest accuracy of 79.39% (p = 0.0008). This is due to the random prediction for entries whose two most similar previous entries belong to different persons. This agrees with the well-known rule of thumb that k should be odd.

The identification accuracy using the weighted voting approach was also computed for 1 to 10 most similar entries. The accuracy using only the most similar previous entry is obviously the same as with the most frequent label approach. For higher k the identification accuracy generally increases until it reaches its maximum of 86.30% at $k = 8$ and then starts decreasing. Again, the differences in identification accuracy between different numbers of the most similar entries used for identification are not statistically significant. Furthermore, the improvement of the weighted over the majority voting is not statistically significant.

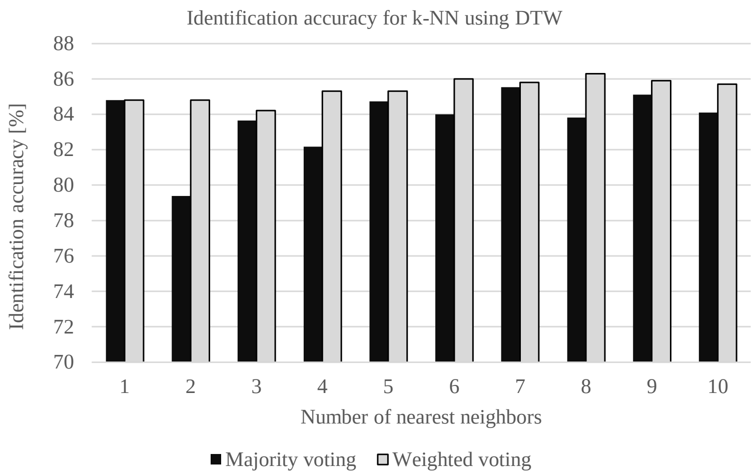

Figure 4. Higher number of neighbors results in higher identification accuracy and weighted voting outperforms majority voting.

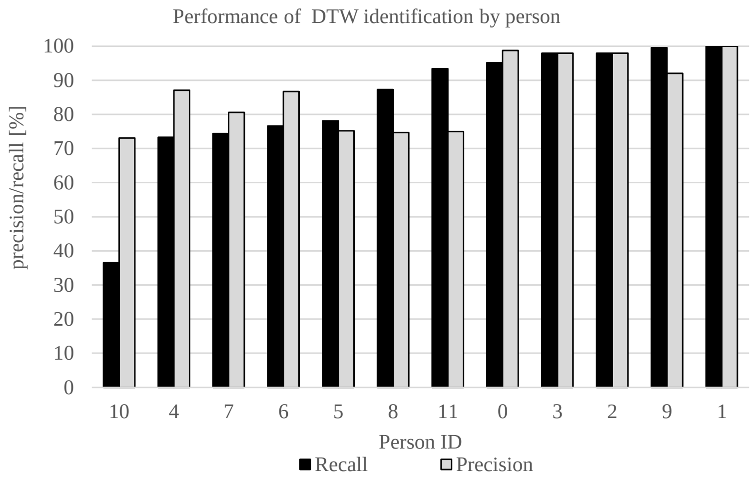

Figure 5.Recall and precision depend on the person being identified.

The performance of identification using DTW varies depending on the person being identified (as shown in Figure 5). Except for one person (no. 10), recall is above 70% with the median 90.36%. The persons that have a more specific way of entering are identified with recall close to 100%. Minimal precision is 73.08% and median is 86.90%. DTW identification suffers from the same problem as the ML approach: it often misclassifies the three pairs of people who are entering the door in a similar way.

6.3. Comparison

The dynamic time warping (DTW) approach has identification accuracy 86.30% and outperforms the ML approach with custom feature extraction and selection, which results in 83.68% accuracy with the *k*-NN algorithm. The *p*-value of the one-tailed Z-test for two-proportions is 0.0506. The comparison between the DTW and the other ML algorithms shows that the difference is statistically significant (with *p*-value 0.05) in that DTW outperforms the other ML algorithms. However, the final results are very similar and the difference could be due to overfitting. For instance, the accuracy of SVM without feature selection is 84.88% which is not significantly worse than the result obtained with DTW.

Regarding the source of misclassification, there is a difference between the DTW and the ML approach. The three pairs of similar people (IDs 10-11, 4-5 and 6-8) are the source of 9.63% of misclassified entries using DTW, while they cause only 6.55% of entries to be misclassified using the ML approach. This might be due to the fact that DTW stretches the time axis and hence loses the information about the duration of (phases of) entry. On the other hand, DTW is better in distinguishing people with different ways of entering. Those cause 4.07% of instances to be misclassified with DTW, while the value for ML is 9.76%. This could be due to the fact that the amount of information given to the ML in the form of the extracted features is limited compared to the complete information about the time series used by DTW. In summary, DTW makes most misclassification between pairs of similar people, while the misclassifications are more evenly distributed with the ML approach. Therefore, a combination of the two approaches might prove to be useful.

7. Conclusions

The paper presented a novel approach to identify a person entering a room (e.g., home or office) using the acceleration signal produced by the door movement. To the best of our knowledge, this is the first attempt to identify a person using door accelerations. Therefore, we also patented the approach at the Slovenian national patent office [25].

In the paper, we compared two approaches: the classical machine learning (ML) with domain-specific features and dynamic time warping (DTW). The results show that both approaches perform similarly, with DTW achieving somewhat better accuracy of 86.3% compared to the 83.7% achieved by the ML approach. The results also show that identification accuracy significantly varies across different people and that some pairs of people are often mutually misidentified (for example person 10 and 11). Furthermore, the results were obtained in laboratory circumstances for single entries without complications. In real-life, people sometimes enter in pairs or enter in a specific way, e.g., when carrying a heavy object. These issues need further attention before practical applications are considered.

Although the identification accuracy is not high enough for a secure access-control applications, the proposed approach is novel and the results are promising for application when slightly lower accuracy is not problematic. Moreover, the approach is completely unobtrusive to the user and can therefore be used as an assistive technology or a smart-home sensor in offices and homes with limited number of people to enable smart-home automation personalization.

In future, we first plan to improve the identification accuracy by combining the two approaches with advanced meta-learning techniques such as Stacking [26]. First analysis shows additional 3.1% improvement when combing both approaches. Second, we plan to analyze the acceleration signal in frequency domain using Fast Fourier Transformations. Another significant improvement should be enabled by classifying only members of a typical family. Accuracies over 90% are achieved in these experiments [27]. We are recording a dataset of door entries during normal use that will be analyzed in future work – the accuracy might decrease due to occasional unusual entries (e.g. when carrying a heavy object). Finally, we plan to improve the computational performance of the DTW approach by comparing the identified entrance signal only with the most representative labeled entries of each person instead of comparing with the entire database of examples. This can be done by clustering the entry signals of each person and using only the cluster centroids or by calculating an average entry signal to represent each person.

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