Transfer Learning Approaches for Gait-Based Wireless Person Identification

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***Abstract*—The human gait is a biometric feature that is unique to any individual. Since the human body affects the propagation of wireless signals, wireless networks can be used for identification of persons walking nearby. This biometric identification approach has been object of research in several studies described in the literature. In this brief, we present a gait-based wireless user identification system that outperforms these existing solutions in terms of cost, effort and accuracy. Firstly, using a mesh network of low-cost wireless sensor nodes, the identification error rate could be reduced by more than 80 % in comparison to the best of prior studies. For a set of six persons to be identified, the identification accuracy could thus be improved to more than 99 %. Secondly, using the technique of Transfer Learning, the capabilities of the proposed system can be easily transferred to identify unknown persons and locations with only a few minutes of training effort. Training the system on the identification of six unknown persons, it has been found that the training effort can be reduced by about 96 % without a significant loss of accuracy.**

***Index Terms*—Convolutional neural network, gait recognition, person identification, transfer learning, wireless sensor network.**

I. Introduction

IDENTIFICATION of individuals is literally a key part of many everyday situations such as for authorization. An example application could be a room or a building only certain persons are allowed to enter. Besides object-based (e.g., by using a key) or knowledge-based (e.g., by using a password) approaches, biometric characteristics play an important role for a variety of applications [1]. Face unlocking features of modern gadgets like smartphones are typical examples for this.

The human gait, i.e., "a person's manner of walking" [2], is one of the lesser-known biometric characteristics of a person. However, since the gait is unique to any individual [3], [4], it can be used for identification purposes. So far, different approaches to capture a human's gait have been described in the literature [1]. One passive approach is based on what is usually referred to as *wireless sensing* [5], [6]: The presence of a human affects the signal propagation within a wireless network. A human's gait is unique and so is the influence of a walking person on wireless networks nearby. Consequently, several identification systems have been studied [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] that make use of this biometric characteristic. An overview about the achieved accuracies is given in Fig. 1.

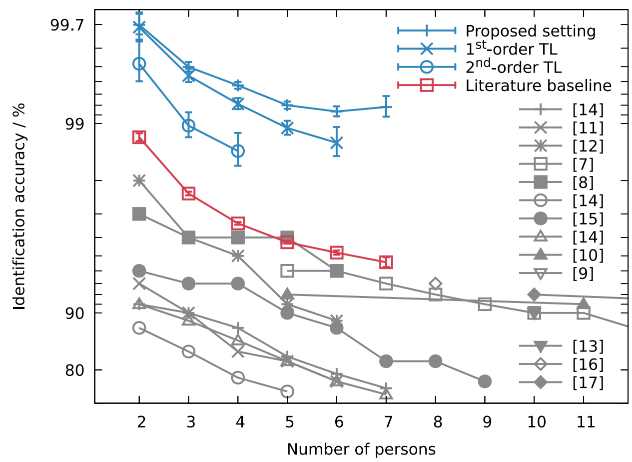

Fig. 1. Identification accuracies described in the literature [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] in comparison to the main results of this contribution. In [14], three different setups have been evaluated all of which are shown in the figure. The meaning of the *literature baseline* is explained in Section IV-B.

In all these studies, several test subjects walked along a given path near an installed wireless network. Usually, the persons had to cross the Line of Sight (LOS) between the transmitter and the receiver [7], [8], [9], [10], [11], [12], [13], [14], [15] but also studies have been described in which only reflections from the subjects were analyzed [16], [17]. In order to identify a person from the recorded data, a variety of different machine learning approaches was presented. So far, the best identification results, like an accuracy of 94.8 % for 6 observed persons [8], were achieved using a Convolutional Neural Network (CNN).

Apart from the signal analysis, a majority of the described systems [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] used a very simple network topology. Such a typical network consisted of a single transmitter-receiver WiFi [18] pair only that was mounted in a low height near the floor. So far, in only a single study [7], the use of a mesh network of multiple IEEE 802.15.4 sensor nodes was evaluated that were mounted in different heights. Although the authors used a rather simple machine learning technique, proper results were achieved like an accuracy of 94.4 % for 6 observed persons.

A major disadvantage especially of Deep Learning (DL) based systems like [8] is the training effort that is needed to

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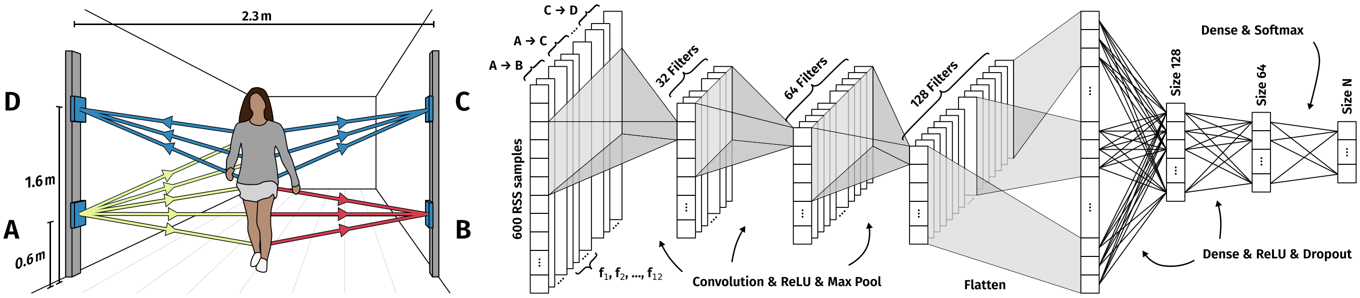


(a) Measurement setup. (b) The kernel size was 3 and the pool size was 2. The dropout rates were 0.2 and 0.1, respectively.

Fig. 2. The measurement setup (a) and the CNN architecture and the corresponding data shapes (b) used in this brief.

achieve a reasonable identification performance. However, as it is the case for other biometric identification techniques like fingerprints or face recognition, a maximum of only a few minutes of setup effort is reasonable for practical use.

In this brief, we propose two major improvements for the use of gait-based wireless identification systems. Firstly, we combine the advantages of state-of-the-art pattern recognition DL algorithms like [8] with a mesh network topology used during data collection as in [7]. Moreover, in contrast to [7] and the majority of prior studies [8], [9], [10], [11], [12], [13], [14], [15], we do not only analyze signals that transmitted the persons but also take into account the reflections from these subjects. Contrarily to all prior work where only unidirectional connections were used, we further propose a bidirectional sampling of the wireless signals in order to enhance the efficiency of the system.

Doing so, we achieved an identification accuracy of 99.1 % for 6 persons to be identified, which is a significant improvement in comparison to all prior studies. For the described mesh network, we designed low-cost Bluetooth sensor devices [19] that have been built around off-the-shelf Bluetooth components only. Therefore, the proposed system could be implemented also with several distributed devices of the Internet of Things (IoT). As a consequence, existing wireless infrastructure may be used for identification purposes in the future.

Secondly, we propose the use of Transfer Learning (TL) to achieve high identification accuracies while only a small amount of training data is available. In a first scenario, a pre-trained network is considered that can identify persons who walk through the given setup. We then transfer the capabilities of this system to a set of previously unknown persons using only a small amount of training data. We refer to this as *first-order TL*. This way, with a training effort of less than two minutes per person, an identification accuracy of 98.7 % for 6 subjects has been achieved.

For practical use cases, however, not only unknown persons have to be learned by the system but also unknown environments of the wireless network have to be considered. In a second scenario, we hence pre-train a network on the identification of multiple persons in multiple different locations. Afterwards, we transfer the network's knowledge to a setup with previously unknown persons at an unknown location. We refer to this as *second-order TL* in the following. This turned out to be more challenging than the TL of first order. However, with a training effort of less than four minutes per person, we still achieved an identification accuracy of 98.6 % for 4 subjects to be identified.

The rest of this brief proceeds as follows. In Section II, a description of the prototype system and the used sensor devices and their configuration is given. The data preprocessing is described in Section III-A. In Section III-B, we discuss the bidirectionality of the data. The architecture of the used CNN is described in Section III-C followed by the details about the TL implementation in Section III-D. Finally, the individual contributions of this brief and their impact are studied within a thorough evaluation of the proposed identification system in Section IV followed by a conclusion in Section V.

II. System Setup

For the prototype system, four wireless transceivers, denoted by A, B, C and D, have been used that were mounted at opposite walls of a floor. A drawing of the setup is given in Fig. 2a. In the example scenario shown in the figure, sensor A emits a wireless signal. Most prior work [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] considered measurements from the connection of a single pair of wireless nodes (A $\rightarrow$ B) only. Contrarily, measurements from within the whole mesh network are used in this contribution. For this, low-cost and low-power Bluetooth sensor devices have been built. Since these devices use an off-the-shelf Bluetooth System on Chip (SoC), their functionality can be implemented with other commercially-available IoT devices as well. A description of these sensor devices can be found in [19].

The devices span a mesh network in which every device transmits subsequently on 12 different carriers $f_1, f_2, \ldots, f_{12}$ while all other devices are listening to the transmitted packets and sampling the Received Signal Strength (RSS). This way, the total packet rate of 5 kHz [19] is divided by the number of devices and the number of used channels. We hence get RSS samples for all $4 \cdot 3$ connections on all 12 carriers with an overall sampling rate of about 104 Hz.

The carrier frequencies were selected according to $f_i = 2411\,\text{MHz} + (i-1) \cdot 6\,\text{MHz}$. For a carrier frequency f and a transmitting device T, we denote the RSS samples that were measured by device R by $r_{f,T,R}$ in the following.

III. System Architecture

A. Data Segmentation and Normalization

Within the described mesh network, the data streams $r_{f,T,R}(t)$ are recorded while different persons are individually walking through the setup. A necessary preprocessing step is the segmentation of the data, i.e., the restriction of the continuous data streams to the interesting parts where a person was actually passing by. For this, we adapted the threshold-based segmentation approach described in [15].

From this segmentation stage, we get several so-called *records* each of which belongs to a certain time window during which a certain person was passing the setup. Each record, in turn, holds all RSS samples $r_{f,T,R}(t)$ for all carriers $f \in \{f_1, \ldots, f_{12}\}$ and all transceivers $T, R \in \{\mathrm{A}, \ldots, \mathrm{D}\}$ that were recorded during that time. Here, each record was assembled from 600 subsequent packets (about 6 s).

The working principle of the presented identification system is to recognize unique patterns in the temporal course of the data. In order to concentrate on these patterns and to make the identification independent of the DC offset of the signal and the overall strength persons affect the measurements, we propose to normalize each data stream from each record with respect to the average (becomes 0) and standard deviation (becomes 1). Doing so, there is little benefit from further normalization techniques such as batch normalization [20].

Contrarily to all prior studies [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], no further preprocessing is applied to the data. This way, any kind of feature selection is completely done by the neural network itself.

B. Bidirectional Measurements

All connections within a record are measured bidirectionally. Theoretically, two corresponding measurements should be equal, i.e., $r_{f,T,R} = r_{f,R,T}$ should hold for all valid combinations of T and R. However, the measurements feature some kind of statistical error $w_{f,T,R}(t)$. According to [21, Proposition 9.12], we have $r_{f,T,R} - r_{f,R,T} = \sqrt{w_{f,T,R}^2 + w_{f,R,T}^2} \not\equiv 0$ what means that the bidirectional records hold more information than it would be the case for unidirectional records. However, since both measurements will be highly correlated with each other, they do not add as much information as measurements from completely different records. Adding all bidirectional data to the input vector of the network would significantly enlarge the number of parameters of the neural network and, hence, would make the network harder to train.

Instead, we propose to split each bidirectional record $\{r_{f,T,R}(t) : T \neq R \in \{A, B, C, D\}\}$ into two unidirectional records $\{r_{f,T,R}(t) : T < R\}$ and $\{r_{f,T,R}(t) : T > R\}$, where the relations $<$ and $>$ refer to alphabetical order, i.e., the first set holds all measurements from the connections $\mathrm{A} \rightarrow \mathrm{B}$, $\mathrm{A} \rightarrow \mathrm{C}$, ..., $\mathrm{C} \rightarrow \mathrm{D}$ and the second set holds all the measurements from the remaining connections $\mathrm{B} \rightarrow \mathrm{A}$, $\mathrm{C} \rightarrow \mathrm{A}$, ..., $\mathrm{D} \rightarrow \mathrm{C}$. This way, the number of available records is doubled. The effect of this is evaluated in Section IV-A.

C. Convolutional Neural Network

In order to identify individuals from given records, we propose the use of a typical CNN which has been proven to achieve good performances in pattern recognition [22]. The input vector consists of the preprocessed (see Section III-A) RSS samples from the 600 packets each record has been assembled from. The number of different connections and carriers in a single record defines the depth (channels) of that input vector. The used CNN consists of three one-dimensional convolutional layers with Rectified Linear Unit (ReLU) activation each of which is followed by a one-dimensional max-pooling layer. After flattening, two fully connected (Dense) layers with ReLU activation and dropout are staged. The final Dense layer comes with a softmax activation and represents the output vector of the network. All details can be seen in Fig. 2b.

Throughout the rest of this brief, Adam optimizer [23] with an initial learning rate of 10^{-3} was used for training. The batch size was 32. All stated identification accuracies are averaged results where the average is calculated over all possible combinations of input data, several repetitions of the training and evaluation process, and a ten-fold cross-validation with regard to the train-test data split. All models have been trained in 15 epochs each.

D. Transfer Learning

In order to train the CNN from Section III-C on the identification task discussed above, measurement data from all persons to be identified are needed. However, the amount of data records needed is critical, as a huge training effort hinders the practical use of the proposed system. One possibility to reduce the amount of necessary training data is the use of Transfer Learning (TL) [24]. This way, the knowledge learned by a trained neural network (base model) can be partially transferred to a another network (transfer model) as long as both networks have some common structure. The training of the transfer model on a task similar to the base task is then usually much faster than it has been with the base model [24].

For the particular TL application in this contribution, i.e., both the first-order and the second-order TL approach mentioned in the introduction, the base model is prepared by training the CNN from Section III-C. For the transfer model, all convolutional layers from this pre-trained model are frozen and all fully connected layers are reset. Afterwards, the transfer model is trained on its new task as it is described in Sections IV-C and IV-D.

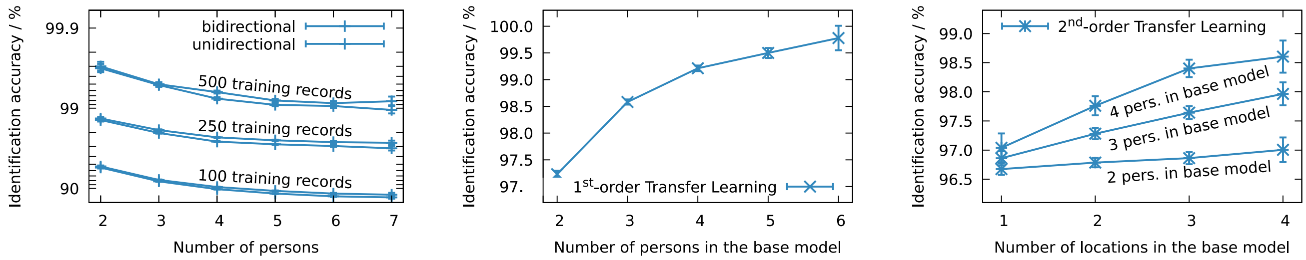
IV. Results

A. Effect of Bidirectionality

At first, an evaluation of the base model, i.e., the presented identification approach without any TL attempts, is discussed. For this, a total of seven persons were asked to walk through the presented setup 600 times each. The results for different numbers of training records for both bidirectional and unidirectional measurements can be seen in Fig. 3a.

As it is expected, the overall accuracy increases with the number of records per person. As it has been described in Section III-B, the number of records can be doubled using the bidirectionality of the proposed mesh network. Of course, as it can be also seen in the figure, the corresponding increase in accuracy is not comparable to the use of twice the amount of real records. Nevertheless, a certain improvement can be recognized though: Using 100 records per person, the performance improvement by bidirectionality has been about one percentage point (the identification error rate has been reduced by 7.2 %). This improvement of the error rate increases to 14.7 % and 22.1 % for 250 and 500 records, respectively.

As it was mentioned earlier, the proposed system can be built entirely from off-the-shelf wireless components. This makes it possible to reuse existing wireless networks for identification purposes. If such a network already features bidirectional communication, the improvement by the bidirectional sampling discussed above comes at no additional cost.



(a) Base model. (b) 1st-order TL model (c) 2nd-order TL model.

Fig. 3. Dependency on different parameters for the base model (a) and both the 1st-order (b) and the 2nd-order (c) TL model.

B. Baseline and Literature Comparison

In order to find some baseline for later comparison, we removed every connection from the records except for the unidirectional connection between the lower pair of devices A $\rightarrow$ B. This way, the wireless network architecture from most earlier studies [8], [9], [10], [11], [12], [13], [14], [15], [16], [17] could be emulated.

The results are shown as the "Literature baseline" curve in Fig. 1. Especially for higher numbers of involved persons, we are able to reproduce the best of prior results, mainly [8] and [7], rather accurately e.g., with 95.2 % for 6 observed persons. In comparison to that, the usage of the proposed bidirectional mesh network architecture ("Proposed setting" in Fig. 1) leads to a significant accuracy improvement of e.g., about 4 percentage points to 99.1 % in that case, i.e., the error rate has been reduced by about 81 %.

Note that the result for 7 observed persons shown in the figure features a significantly higher error than the results for fewer observed persons. This is due to the fact that there are significantly fewer combinations of data partitions when using data from all persons available in the dataset. As a consequence, the averaged identification result (see also Section III-C) shown in the figure is less accurate in this case. Hence, the slight increase in accuracy for 7 observed persons that can be seen in the figure is not significant.

C. First-Order Transfer Learning

For the TL of first order, a pre-trained base model is retrained with a set of previously unknown persons.

At first, we consider the dependency of the accuracy of the TL model on the number of persons in the base model. For the evaluation, a total of ten persons were asked to walk through the presented setup. Using up to six persons, the base model was trained using 600 bidirectional records per person. After freeze and reset (see Section III-D), four unknown persons, i.e., persons not used for base model training, were used to train the TL model with only 20 bidirectional records per person. The results can be seen in Fig. 3b. A proper identification accuracy of 99.2 % was achieved for four persons in the base model. Moreover, the accuracy continues to increase by increasing number of persons in the base model. This is the expected behaviour since the feature extraction capabilities of the base model are expected to enhance/generalize as the number of persons in the base model increases.

For the sake of better comparability, we further consider the dependency on the number of persons in the TL model. Using four persons in the base model, we trained different TL models with up to six persons. The results can be seen in the introductory Fig. 1. Although only 20 training records (about two minutes of training data) were used per person, the identification accuracy is comparable to that one of the base model ("Proposed Setting" in Fig. 1) where 500 records were used per subject. For example, an accuracy of 98.7 % was achieved for six persons to be identified.

D. Second-Order Transfer Learning

For practical use, also changes in the location of the setup should be considered. For the evaluation of this second-order TL, we asked four persons to walk through the given setup at four different locations each. From this, different base models were trained with varying numbers of persons and locations using 150 bidirectional records per person and location. The used locations differed in several aspects from each other such as the height of the surrounding room or the construction of the walls (concrete/dry). In two of the locations used, the setup was installed in the center of a large room with even no walls behind the sensing devices.

For the transfer model, four additional persons were asked to walk through that setup in an additional fifth location. Using only 40 records per person, the TL model was trained on the base of the frozen/reset (see Section III-D) base models. The results can be seen in Fig. 3c. As it is expected, both more persons and locations in the base model lead to higher identification accuracies of the TL model. Even if the base model is trained only at a single location, the TL model achieves a proper accuracy for the unknown (fifth) location. Nevertheless, the accuracy significantly increases with an increasing number of locations in the base model.

The dependency on the number of persons in the TL model can be seen, again, from the introductory Fig. 1. While the overall accuracy has decreased in comparison to the base model's performance and the first-order TL described above, we still perform significantly better than what is described in the literature. For four persons to be identified, an identification accuracy of 98.5 % is achieved by the TL model. For this, less than four minutes of training data are used.

V. Conclusion and Outlook

Several aspects of improving the accuracy of gait-based wireless person identification systems have been discussed in this brief. Firstly, it was shown that using the proposed bidirectional wireless mesh network architecture leads to significant accuracy enhancements in comparison to all prior work [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17]. Using a CNN for signal analysis and classification, the identification accuracy for six observed persons could be improved by about 4 percentage points from about 95 % (literature baseline) to more than 99 %. That is, the identification error rate was reduced by more than 80 % using the proposed improvements.

Secondly, applying the technique of Transfer Learning, we got this interesting biometric identification approach closer to real-world applications. In a first stage, a pre-trained model was trained on the identification of previously unknown persons. Although the identification accuracy has not worsen much (0.4 percentage points), the training effort could be reduced by 96 % to about two minutes of data recording per person. In a second stage, we trained a pre-trained model on the identification of previously unknown persons while also the setup was installed at a previously unknown location. Although only four minutes of training effort was spent by every of the four test subjects, an accuracy of still 98.5 % was achieved.

Moreover, the results (Figs. 3(b) and 3(c)) promise further accuracy enhancements if the number of persons and locations in the base models is increased. Due to the limits of the recorded data set [25], this could, however, not be tested so far but may be object of future study.

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