Behavioral Biometric-Based Human Identification from 3D Skeletal Motion Using Convolutional Neural Networks

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ABSTRACT

Accurate and reliable human identification is needed to provide personalized services in conjunction with current and future technological developments. This study presents a motion-based human identification approach that utilizes 3D skeleton data to capture unique individual motion patterns. Joint coordinates are processed to extract spatial and temporal features through two Convolutional Neural Network (CNN) models with different depths. Evaluation on the UTKinect-Action3D dataset (20 joints, 10 subjects, nine actions) shows that the deeper model achieves 98.25% accuracy, whereas the lighter model achieves 96.97%. To assess generalization, both models are further tested on the Florence 3D Actions dataset with 15 joints, achieving accuracies of 85.53% and 83.55%, respectively. These findings confirm that detailed motion representation significantly improves identification performance and demonstrate that CNN-based models can effectively recognize individuals based on body motion patterns.

Keywords-biometrics; CNN; identification; skeletal

I. INTRODUCTION

Personal services are currently widely provided in various applications, both in device personalization applications and in the field of intelligent surveillance and security. Thus, reliable and accurate human identification is needed. An approach that can be used is motion-based identification, which utilizes the uniqueness of human activity patterns as distinguishing features between individuals. Every human movement—such as sitting, standing, waving, or clapping—has unique characteristics for each individual. Factors such as rhythm, tempo, and movement dynamics can be utilized in behavioral biometrics. Traditional physiological biometrics, such as fingerprints or iris, are intrusive and require direct interaction. Behavioral biometrics are non-intrusive and, without user awareness, allow continuous observation, making it ideal for convenient identification systems that are resistant to spoofing attacks.

This study presents a human identification approach based on the uniqueness of skeletal movement patterns in a 3D space using Deep Convolutional Neural Networks (DCNNs). The model automatically learns discriminative features from motion data represented by 3D skeletal joint coordinates. Using the convolution method, the model is designed to capture both spatial and temporal patterns, resulting in an accurate, practical, and scalable identification system. The main contributions of this study are as follows:

1. Presents a novel approach to individual identification based on typical human movements during activities using 3D skeletal data.
2. Designs a CNN approach that can be applied to skeletal movement data streams as video representations to identify humans automatically.
3. Designs and tests two CNNs trained on two public datasets to evaluate and compare their reliability.

II. RELATED WORKS

Human identification through biometrics is increasingly gaining attention and has been widely used in various fields, such as security, healthcare, and service personalization. Various biometric techniques continue to emerge, ranging from gait and sitting style to voice recognition. A widely used approach is to recognize human movement activities through video data, motion sensors, or data based on human skeletal movements during activities. In this approach, deep learning plays an important role in extracting features from time series data by capturing the spatial and temporal characteristics of each individual in more depth, either through Long Short-Term

Memory (LSTM) or CNN-based networks. Although manual observation of movement characteristics can be used, traditional methods rely heavily on subjective judgment and expert knowledge.

Several studies utilize human motion data recorded through depth cameras and RGB videos. For example, in [1-5], deep learning models were used to recognize human actions from visual data. In [6], activity recognition from radar signals was investigated. In [7-12], data from wearable sensors were used to identify human movement patterns. In [10], a gait-based identity recognition method was used specifically for older people. In [13], the classification of daily physical behavior in adults over 70 years of age was explored, distinguishing between walker users and non-users using accelerometer data. Motion sensors such as accelerometers and gyroscopes are used to measure acceleration and angular velocity, which are then used to extract essential features in recognizing unique patterns of human movement. In [8], these data were used to build a machine learning-based identification model. In [14], hybrid deep learning approaches, such as SpatioTemporalNet (STNet), were developed to analyze static and dynamic features of physiological biometrics, such as fingerprints, in a real-world context. In [1], a regional-LSTM model was developed to recognize rhythmic gait patterns over two seconds, which was used to identify and re-identify individuals.

With the advent of deep learning, particularly DCNNs, there has been a shift towards automated feature extraction from 3D skeletal data. Several studies have proposed the use of CNN combined with LSTM to model motion sequences [2, 6, 15-17], including gait. Other approaches employ Recurrent Neural Networks (RNNs) to capture temporal dynamics [18, 19]. However, most of these approaches focus on general motion pattern recognition and have not explicitly emphasized individual idiosyncrasies in the context of specific activities to identify individuals.

This research builds on the understanding of behavioral biometrics by utilizing DCNN as the main architecture to identify individuals based on their 3D skeletal movement characteristics. The main objective was to develop an identification system that is more accurate, adaptive, and resilient to disturbances from the real environment.

III. PROPOSED METHOD

The proposed method for identifying humans is developed based on deep learning, specifically CNN. Figure 1 describes the stages of identifying 10 actors from 3D skeletal motion data.

A. Data Acquisition and Preprocessing

Skeletal 3D coordinate data were acquired by extracting human activity videos from 10 actors. In the preprocessing stage, data augmentation was performed to produce video identity information, using 10 activities with 20 subjects (actors) and 20 joint positions (x, y, z) that describe skeletal movements. Figure 2 shows how data acquisition was carried out. Skeletal movement data were collected from ten actors, each performing a series of pre-defined human actions once. Each recording consisted of a series of frames, with each frame containing the 3D coordinates of 20 skeletal joints representing the subject's posture at a given time. As a result, a total of 20 skeletal movement files were obtained. Frame-wise action labels from a separate file were aligned with skeletal data based on frame indices, allowing supervised training per activity class. Individual frame files were consolidated into a unified, frame-level labeled dataset for deep learning-based activity recognition. The resulting dataset includes both spatial features (3D joint positions) and temporal labels (action classes), which form the basis for developing robust models for action classification or human identification tasks.

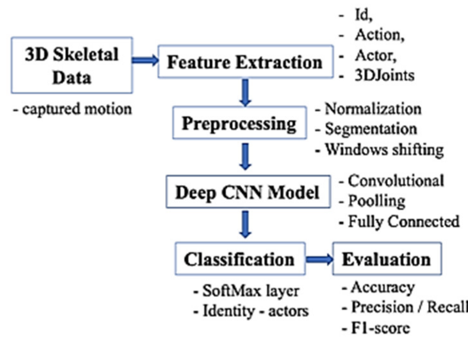

Fig. 1. Flow diagram of human identification from 3D skeletal motion.

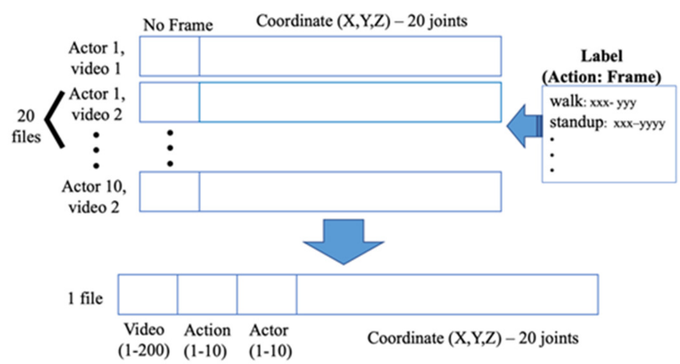

Fig. 2. Temporal annotation and integration on multi-actor 3D skeletal motion data for supervised behavioral biometrics.

B. Windows Shifting

Human motion during an activity is characterized by continuous changes in joint positions across consecutive video frames. The system calculates the change in motion coordinates (x, y, z) for each frame sequence using the Euclidean distance to capture the dynamic motion pattern. To prepare the input for the model, the joint sequences are segmented using a fixed-size sliding window of 16 frames per video. This window size is chosen to capture meaningful temporal information related to a single instance of an activity performed by a subject. During preprocessing, each windowed segment is paired with a corresponding actor label, which serves as the output class for the supervised learning task. A sliding window along the temporal axis generates overlapping segments to capture motion transitions, which are then used for model training and evaluation.

C. Model Architecture

To handle multi-class classification, this study employs a CNN comprising two convolutional layers and subsequent fully connected components. The first layer applies a 2D convolution with 32 filters of size 3×3, using ReLU activation and 'same' padding to preserve the spatial dimensions of the input data, which has a shape of (16, 20, 1). Subsequently, the model performs a 2×2 max pooling operation to halve the spatial dimensions of the output. The second convolutional block consists of a convolutional layer with 64 filters (3×3, ReLU, same padding), followed by a 2×2 max pooling, which further reduces the spatial dimensions. The model then flattens the resulting feature maps into a one-dimensional vector. The vector is fed into a dense (fully connected) layer with 256 neurons using ReLU activation, followed by a dropout layer (rate = 0.3) for regularization. A subsequent dense layer with 128 units is added before the final output layer, which consists of 10 neurons with softmax activation, allowing the model to output class probabilities for a 10-class classification task.

Algorithm 1 describes the process of identifying humans using skeletal motion data. The dataset of 10 actions, represented by changes in the 3D coordinate distances of 20 joints and labeled with 10 actors, undergoes segmentation using a shifting window of size 16. The data split allocates 80% for training and 20% for testing.

```
Algorithm 1: Human identification using
skeletal motion
Input: S={s1, s2, s3, …, s20}
  W ← 16 # shifting window size;
  L ← 1..10 # label - actor identity
Output: Predicted human identity (10)
Data Preprocessing (normalize;
  segmentation; reshape)
S ← Euclidean Distance
Shifting windows (S, W)
Feature Extraction: spatial and temporal
  patterns
Data Split (training: 0.8; testing: 0.2)
CNN: Model 1 or Model 2
Classification:
  Fully connected layer
  Identity (L) ← SoftMax layer
Optimize (Adam)
Evaluation - Performance Metrics
```

Two CNN models, Model 1 and Model 2, were used, with their architectures described in Tables I and II. Model 1 includes deeper layers and higher-dimensional dense units, thus requiring higher training time and inference latency. Model 2, with much fewer parameters, offers faster execution, making it more suitable for deployment in real-time or resource-constrained environments.

TABLE I. BEHAVIORAL BIOMETRIC BASED HUMAN IDENTIFICATION ARCHITECTURE - MODEL 1

Layer	Output shape	Param #
Conv2D	(None, 16, 20, 32)	320
MaxPooling2D	(None, 8, 10, 32)	0
Conv2D	(None, 8, 10, 64)	18496
MaxPooling2D	(None, 4,5, 64)	0
Flatten	(None, 1280)	0
Dense	(None, 256)	327936
Dropout	(None, 256)	0
Dense	(None, 128)	32896
Dense	(None, 10)	1290

TABLE II. BEHAVIORAL BIOMETRIC BASED HUMAN IDENTIFICATION ARCHITECTURE - MODEL 2

Layer	Output Shape	Param #
Conv2D	(None, 16, 20, 16)	160
Maxpooling2D	(None, 8, 10, 16)	0
Conv2D	(None, 8, 10, 32)	4640
Maxpooling2D	(None, 4, 5, 32)	0
Dropout	(None, 4,5,32)	0
Flaten	(None, 640)	0
Dense	(None, 64)	41024
Dense	(None, 10)	650

IV. EXPERIMENTS

All experiments were carried out on macOS Monterey, with a 1.6 GHz Dual-Core Intel Core i5 processor and 8 GB 2133 MHz LPDDR3 memory.

A. Dataset

The data in this experiment were from the public UTKinect-Action3D dataset [20], originally introduced in [21]. The dataset contains activity videos with a frame rate of 30 fps from 10 actors. Each actor repeats 2 times 10 activities (walk, sit down, stand up, pick up, carry, throw, push, pull, wave hands, clap hands). The skeletal data in the dataset consist of 20 joint points. To further evaluate the robustness of the model, the Florence 3D Actions dataset [22], originally introduced in [23], was used. The dataset consists of 10 subjects (actors) performing nine activities (wave, drink from a bottle, answer phone, clap, tight lace, sit down, stand up, read watch, bow) which were recorded repeatedly 2 to 4 times, resulting in 215 videos. For each action, there is 3D skeleton coordinate data from 15 joints. Figure 3 shows the joint positions of both datasets.

B. Evaluation Metrics

Confusion matrices were used to calculate four key metrics, accuracy, precision, recall, and F1-score, to evaluate models' performance. These metrics are defined in (1)–(4). Accuracy is the proportion of correctly predicted instances out of all predictions made. Precision and recall evaluate the model's ability to recognize positive instances correctly. F1-score merges precision and recall into a single, unified metric that provides a more balanced assessment, particularly useful when dealing with imbalanced class distributions. Model performance results were validated using cross-validation to provide confidence in the developed model.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP+FP})} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP+FN})} \quad (3)$$

$$\text{F1}-\text{score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

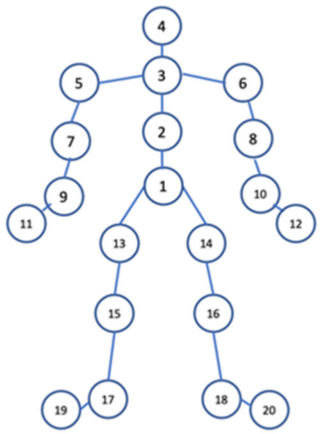

Fig. 3. Position of 20 joint points (1: hip center, 2: spine, 3: shoulder center, 4: head, 5: left shoulder, 6: right shoulder, 7: left elbow, 8: right elbow, 9: left wrist, 10: right wrist, 11: left hand, 12: right hand, 13: left hip, 14: right hip, 15:left knee, 16: right knee, 17: left ankle, 18: right ankle, 19: left foot, 20: right foot) and 15 joint points (1: head, 2: neck, 3: spin, 4: left shoulder, 5: left elbow, 6: left wrist, 7: right shoulder, 8: right elbow, 9: right wrist, 10: left hip, 11: left knee, 12: left ankle, 13: right hip, 14: right knee, 15: right ankle) in the dataset.

V. RESULT AND DISCUSSION

Figure 4 shows the experimental results on the main dataset using Model 1. Accuracy and loss metrics for both Model 1 and Model 2 were evaluated on two datasets (with 20 joints and 15 joints). Table III summarizes the experimental results for both models across both datasets.

TABLE III. ACCURACY AND LOSS OF 20 JOINTS AND 15 JOINTS IN MODEL 1 AND MODEL 2

	20 joints		15 joints	
	Model 1	**Model 2**	**Model 1**	**Model 2**
Accuracy	98.25%	96.97%	85.53%	83.55%
Loss	0.1206	0.1499	0.9319	0.7447

The reduction in the number of joints leads to a loss of spatial and temporal motion information, particularly in joints that carry important contextual cues for body movement. In both datasets, learning ability tends to improve, but in the second dataset (15 joints), the model is less able to distinguish similar classes, which reduces classification accuracy. However, the accuracy on the second dataset still shows that important information was captured, but the model lost motion resolution.

Achieving 98.25% accuracy across 10 subjects, the proposed CNN-based Model 1 effectively utilizes 3D skeletal motion data. Its robustness is further supported by F1 scores of 0.99 or above for most actor classes. In particular, actor 07 and actor 08 show slightly lower precision and recall, possibly due to overlapping motion features with other actors or higher intra-class variation. Table IV summarizes these detailed performance results. Figure 5 shows a confusion matrix supporting these results, showing who the actual actors are and who the model predicts.

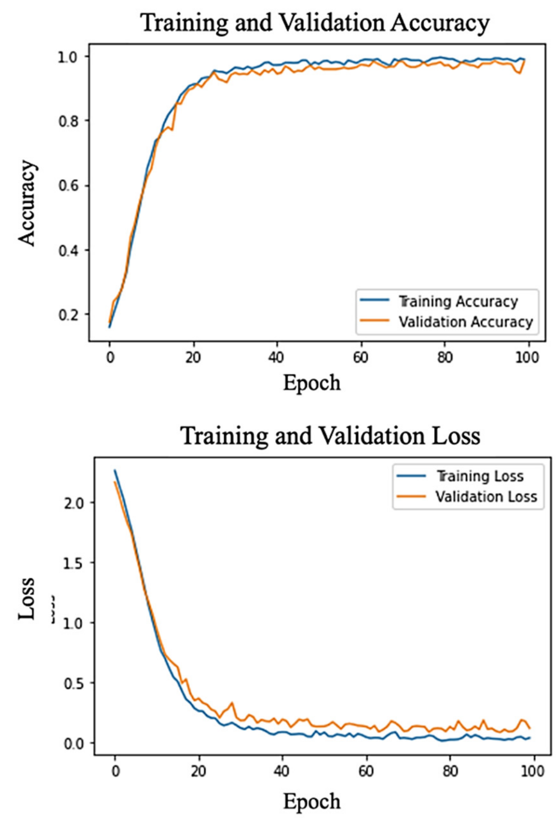

Fig. 4. Accuracy and loss of on Model 1 on the 20 joints dataset.

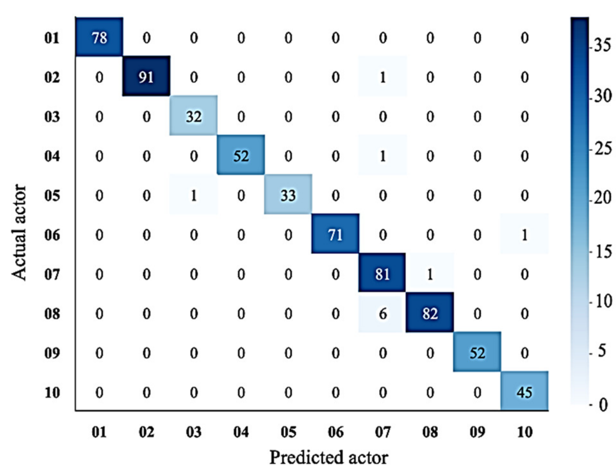

Fig. 5. Confusion matrix for Model 1 on the 20 joints dataset.

With near-perfect identification capability across most classes, the model demonstrates state-of-the-art performance in the context of a limited dataset and 10 subjects. Table V presents the methods of biometrics research that have been proven through experiments and studies.

TABLE IV. BEHAVIORAL BIOMETRICS IDENTIFICATION PERFORMANCE OF 20 JOINTS ON MODEL 1 AND 2

Actor	Precision		Recall		F1-score		Support	
	1	2	1	2	1	2	1	2
01	1.00	0.97	1.00	0.97	1.00	0.97	78	
02	1.00	0.94	0.99	0.99	0.99	0.96	92	
03	0.97	0.97	1.00	1.00	0.98	0.98	32	
04	1.00	0.98	0.98	0.96	0.99	0.97	53	
05	1.00	0.97	0.97	1.00	0.99	0.99	34	
06	1.00	1.00	0.99	0.97	0.99	0.99	72	
07	0.91	0.94	0.99	0.95	0.95	0.95	82	
08	0.99	0.98	0.93	0.93	0.96	0.95	88	
09	1.00	0.98	1.00	0.98	1.00	0.98	52	
10	0.98	1.00	1.00	0.98	0.99	0.99	45	

1: Model 1, 2: Model 2

The lighter version of Model 2, with significantly fewer parameters, achieved 96.97% accuracy, highlighting its potential for real-time applications with limited computational resources. With only a 2% difference in accuracy and much fewer parameters, the lighter and faster model can be useful for implementation in real-world systems. Previous studies have addressed biometric identification through matching algorithms [10], STNet with hybrid optimization [14], LDA-MLP combinations [24], and multimodal integration [25]. This study differs by employing a CNN that focuses on recognizing typical human movement.

TABLE V. STATE OF THE ART METHODS

Study	Methods	Acc (%)
[24]	Evaluated various classifiers with dynamic algorithm combinations. The combination of LDA and MLP outperformed others. The classifier results refer to Naïve Bayes and SVM-L.	92.25, 78.75
[10]	Biometric identity recognition based on elderly users' gait from wearable sensors using a multiple matching algorithm-based method.	96.70
[14]	Biometric identification through fingerprint uniqueness, performed through the integration of STNet and hybrid GAPSO.	98.70
[25]	Identification by integrating multimodal biometrics, cancelable biometrics, and incremental learning (1D-CNN) techniques.	98.92
Proposed method	Uses 3D coordinate data of skeletal movements of 9 activities to identify 10 actors using CNNs.	98.25

VI. CONCLUSION

This research fills an overlooked gap in prior studies that have largely focused on recognizing activities rather than identifying individuals. By employing 3D skeletal motion data, two CNN-based models were designed to capture distinctive spatial-temporal movement patterns. The deeper model achieved 98.25% accuracy on the UTKinect-Action3D dataset, while the lighter model still performed strongly at 96.97% with fewer parameters, making it attractive for real-time use or on devices with limited resources. Additional experiments on the Florence 3D Actions dataset confirmed the robustness of the method, though performance decreased when the number of joints was reduced.

A key contribution of this work is that it shows that skeletal motion can serve as a behavioral biometric for personal identification. In contrast to conventional or multimodal methods, the proposed CNN framework provides a scalable, end-to-end, and non-intrusive solution. These findings strengthen the development of practical biometric systems with potential applications in healthcare, security monitoring, and personalized services. Future studies could extend this framework to larger and more diverse populations and explore deployment on mobile or embedded platforms for real-time implementation.

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