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SPARSE CODING BASED FEATURE EXTRACTION TECHNIQUE FOR PERSON IDENTIFICATION

Jirayu Samkunta[1], Patinya Ketthong[1,2], Nghia Thi Mai[3]
Kotaro Hashikura[1], Md Abdus Samad Kamal[1], Iwanori Murakami[4]
and Kou Yamada[4]

[1]Graduate School of Science and Technology
[4]Division of Mechanical Science and Technology
Gunma University
1-5-1 Tenjincho, Kiryu 376-8515, Japan
{ t222b603; t222b601; k-hashikura; maskamal; murakami; yamada }@gunma-u.ac.jp

[2]Faculty of Engineering
Thai-Nichi Institute of Technology
1771/1 Pattanakarn Road, Suanluang, Bangkok 10250, Thailand
patinya@tni.ac.th

[3]Department of Electrical and Electronic 1
Posts and Telecommunications Institute of Technology
Km10, Nguyen Trai, Ha Dong District, Hanoi 151090, Vietnam
nghiamt@ptit.edu.vn

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Abstract. *Human identification research has been an important topic in various fields, ranging from biometrics to human-computer interaction. However, extracting meaningful information from hand movements to facilitate accurate personal identification remains a significant challenge. This study addresses this challenge by proposing an alternative approach for feature extraction of hand kinematics using a sparse coding technique. A sparse coding technique is utilized to extract hand motion features from time series data, enabling personalized identification of individuals. Despite numerous existing feature extraction techniques, sparse coding offers distinct advantages, including the ability to reduce the number of features while retaining essential information. The proposed method is evaluated using hand kinematics time series data, and its effectiveness is assessed through the Neural Network (NN) classification technique. Experimental validations are conducted to demonstrate and compare the effectiveness of the proposed method against state-of-the-art sparse coding and other feature extraction techniques. The results reveal that the proposed method outperforms existing techniques, achieving significantly higher accuracy in participant identification. Overall, this study presents a novel approach to feature extraction for hand kinematics-based human classification, offering promising implications for various applications, including biometrics and human-computer interaction.*

Keywords: Hand kinematics, Feature extraction, Sparse coding, Neural network classification, Hand kinematics time series, Human recognition

1. **Introduction.** Over the past decade, there has been significant research into Human Action Recognition (HAR) [1] to better understand human behaviors and enable person identification. HAR has found wide-ranging applications, including medical diagnosis, health monitoring, Human-Computer Interaction (HCI), and virtual reality [2, 3]. Human

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actions can be represented through various means, such as visual data, biometrics, and inertial signals [4, 5, 6].

Nowadays, biometrics has emerged as the dominant approach for recognizing individuals by their distinct characteristics. Biometrics is extensively applied across various fields, encompassing criminal investigations, civil identification, consumer authentication, access control, time tracking, public space surveillance, and border security, among others. There exists a multitude of distinctive attributes that can be harnessed for effective person identification. Biometrics methods encompass a wide range of types, including fingerprints, footprints, iris scans, and speech patterns [7, 8, 9, 10].

On the other hand, kinematic data does not inherently entail human identification awareness. Given that kinematic data often comprises numerous features, some of which may be redundant, noisy, or irrelevant, it poses challenges for classification and identification algorithms. To address these challenges, various studies have implemented feature extraction techniques for human identification using kinematic data [11, 12, 13]. Additionally, as kinematic data serves as classification input, its dimensionality becomes considerable, leading to complex and time-consuming processing of the feature vector. Feature extraction processes can mitigate these issues by reducing the dimensionality of feature vectors and simplifying their complexity. Moreover, feature extraction can identify significant features within kinematic data, thereby enhancing the performance of classification and identification algorithms. Addressing the gaps in existing research related to human identification based on kinematic data involves finding feature extraction techniques to improve identification performance.

Feature extraction techniques find widespread application across various research domains, including image processing, mass spectrometry, time series analysis, and automatic text analysis. Among these techniques, Principal Component Analysis (PCA) is commonly employed. PCA utilizes an orthogonal transformation to convert a set of correlated variables into a smaller set of linearly uncorrelated variables known as Principal Components (PCs). Each PC is represented by a vector that encapsulates information from the original variables. By leveraging feature extraction techniques such as PCA [14], researchers can effectively explore and understand the complex kinematic characteristics. This deeper understanding paves the way for advancements in fields such as prosthetics, rehabilitation, Human-Computer Interaction (HCI), and gesture recognition [15, 16].

Given the growing importance of feature extraction techniques, it remains a critical aspect of hand kinematics analysis, holding promising potential for future developments. Expanding on the significance of feature extraction in hand kinematics analysis, feature extraction techniques have an essential role in further enhancing the understanding of complex hand movements. One potent approach in this regard is sparse coding-based feature extraction. Sparse coding has gained prominence in various research fields, especially signal processing applications [17, 18], image and videos processing [19, 20], and reconstruction [21], due to its ability to efficiently represent data with a sparse set of features and basis functions. In the context of hand kinematics, sparse coding offers a promising solution for extracting essential information and significantly reducing the dimensionality of data. Leveraging the advantages of sparse coding can significantly enhance the field of human identification and improve performance of it.

In this paper, we propose an innovative feature extraction technique for person identification based on hand kinematic data in time series format, employing the dictionary learning technique. The structure of this paper is as follows. In Section 2, the dataset is expressed into the intricacies of the hand kinematic data utilized in our study. Section 3 offers the data preparation by using linear interpolation and combined vectors to construct the input matrix. These provide a comprehensive schema of our research, encompassing the feature extraction based on dictionary learning for the subsequent classification. Section 4 presents the experimental apparatus that explored the overall research methodology, experimental configuration, and experimental results of the proposed method in person identification. In the concluding Section 5, we summarize our findings and highlight potential avenues for future research and enhancements in the realm of hand kinematics analysis, leveraging sparse coding and machine learning techniques.

2. **Dataset.** The UNIPI dataset [22] consists of hand kinematics data obtained from visual sensors, to investigate postural synergies in human grasping. The dataset is collected by involving six subjects, each tasked with grasping various objects, thus exhibiting distinct hand posture behaviors that are subsequently analyzed from a kinematic standpoint. These six participants, comprising three females and three males, fall within the age range of 23 to 27, with a mean age of 25.17 years, and all of them are right-hand dominant. Additionally, it is important to note that none of the participants had any neuromuscular disorders that could interfere with the objectives of the experiment. Before the commencement of recording data, all volunteers provided their informed consent to participate. The statistics presented in Table 1 offer insight into the demographic and health-related attributes of the participants, providing valuable context for the analysis and interpretation of the UNIPI dataset. This study aims to identify person subjects with 6 participants based on hand kinematic data.

TABLE 1. Descriptive statistics of the UNIPI dataset

Indicator	**Value**
Number of subjects	6
Gender (female/male)	3/3
Age range (years)	23-27
Mean age (years)	25.17
Hand dominance	Right
Presence of neuromuscular disorders	None

The data acquisition setup comprises two vital components. Firstly, the Phase Space Motion Capture System is employed to enable the recording of kinematic data through a 3-dimensional motion tracking mechanism facilitated by active LED markers. This system includes 10 stereo cameras that simultaneously track the 3D positions of these active LED markers, which are strategically attached to the hand and phalanges. The kinematic data are recorded at a sampling time of 0.02 seconds. Secondly, the experiment utilized a diverse set of 21 objects for experiments and recorded hand movements, as detailed in Table 2.

The kinematic model of the human hand is inherently complex and challenging to describe comprehensively. In this study, we address this complexity by considering a detailed kinematic model of the human hand, specifically focusing on its 20 Degrees of Freedom (DoFs). The hand kinematic model and comprehensive breakdown of hand kinematics are expressed in Figure 1. We break down the description into four main components, corresponding to the four long fingers (index, middle, ring, and little), each characterized by four angles. For each long finger, we analyze the motion of its joints, involving two DoFs at the metacarpophalangeal joints to describe flexion-extension and abduction-adduction movements, as well as one DoF at both the proximal and distal interphalangeal joints to delineate flexion-extension mobility. The thumb's representation is more complex, encompassing four joints, with two DoFs at the trapeziometacarpal joint for flexion-extension

Table 2. The details of 21 objects

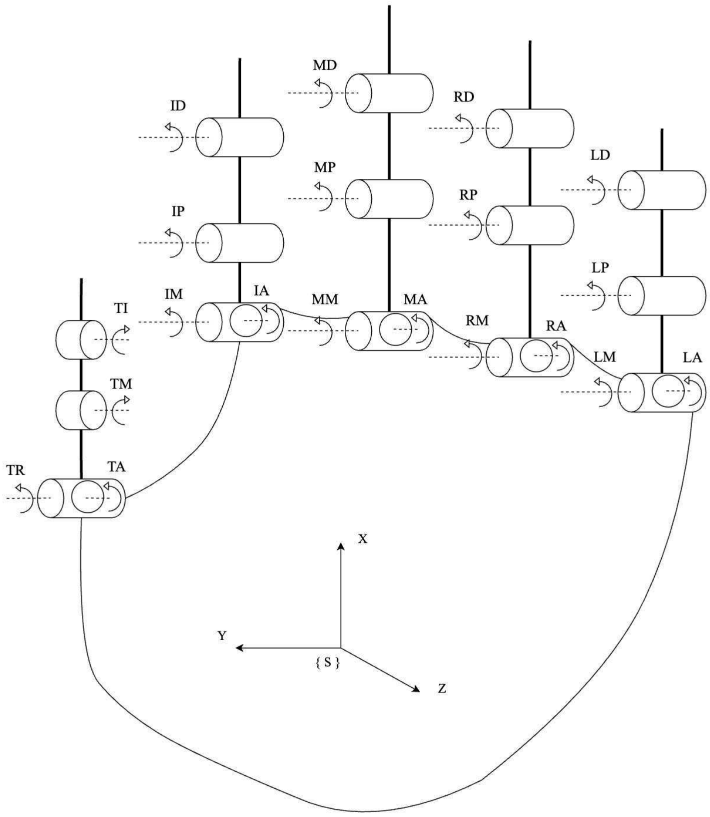
No.	Objects
1	2 Euro Coin
2	Button Badge
3	Key
4	Credit Card
5	CD
6	Comb Hair Color
7	Slat Shaker
8	Tape
9	Chess (Queen)
10	Knob
11	Matchbox
12	Screw
13	Match
14	Cigarette
15	Rubber Band
16	Maker
17	Screw Driver
18	Shashlik
19	Glasses
20	Coffee Mug
21	Plate

and abduction-adduction motions, one DoF at the metacarpophalangeal joint, and one DoF at the interphalangeal joint for flexion-extension mobility. To facilitate our analysis, the hand kinematics is expressed with Denavit-Hartenberg (DH) parameters that are separated to describe thumb and four long fingers based on the kinematic chain of each finger [22].

3. Materials and Methods.

3.1. **Data preprocesosing.** The UNIPI dataset comprises kinematics data recorded in a time series format. Despite having a consistent sampling rate of 0.02 seconds, the individual kinematic datasets vary in length due to the inherent temporal distinctions in each data segment. As previously mentioned, it is imperative to resample these datasets to ensure uniform resolution. To achieve this, we employed linear interpolation as a means to standardize the time series data. In this study, the kinematic data is resampled to consist of 500 samples each. Subsequently, the resampled data is flattened into one-dimensional arrays, resulting in a total of 10,000 features per vector. This transformation effectively converted the time series data into a vector format by linking the next row of data to the subsequent column of the previous row, as depicted in Figure 2. The flattened data, encompassing information from 21 objects, 2 trials, and 6 participants, is consolidated into a matrix with dimensions of 252 rows by 10,000 columns, as illustrated in Figure 3.

3.2. **Sparse coding based on dictionary learning.** The proposed feature extraction strategy is based on sparse coding, providing an alternative approach for extracting features from kinematic data. This technique utilizes a dictionary to match features and extract the necessary information, expressing it as a basis feature vector. Sparse coding



(a)

No.	DoFs	Descriptions
1	TA	Thumb Abduction
2	TR	Thumb Rotation
3	TM	Thumb Metacarpal
4	TI	Thumb Interphalangeal
5	IA	Index Abduction
6	IM	Index Metacarpal
7	IP	Index Proximal
8	ID	Index Distal
9	MA	Middle Abduction
10	MM	Middle Metacarpal
11	MP	Middle Proximal
12	MD	Middle Distal
13	RA	Ring Abduction
14	RM	Ring Metacarpal
15	RP	Ring Proximal
16	RD	Ring Distal
17	LA	Little Abduction
18	LM	Little Metacarpal
19	LP	Little Proximal
20	LD	Little Distal

(b)

FIGURE 1. (a) Hand kinematics model based on 20 Degrees of Freedom (DoFs); (b) the descriptions of the hand kinematics model with 20 DoFs

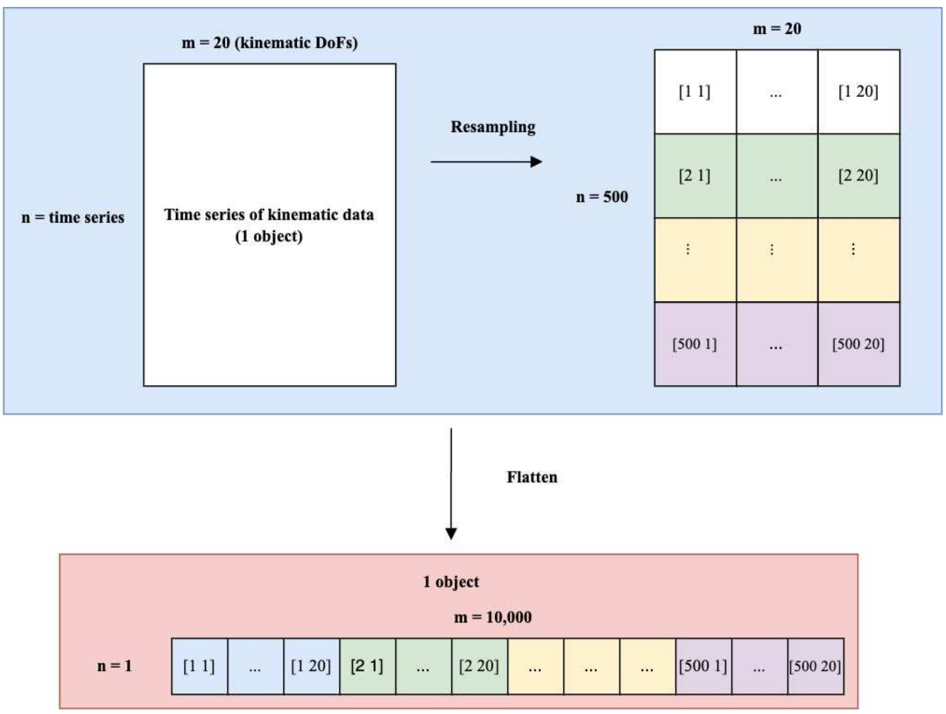


FIGURE 2. Resampling and flatten processes

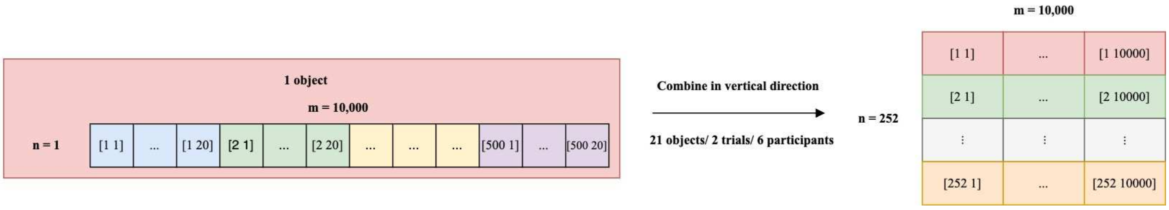


FIGURE 3. Combined vectors process

is fundamentally a learning method that can yield a sparse representation of data by preserving the combinations of basic elements that constitute a dictionary. The key idea of the proposed method is to use dictionary learning techniques for feature extraction that are implemented in the processes of human classification and recognition from hand kinematic time series data. Initially, an initial dictionary is created by randomizing from raw data, followed by a data preprocessing step. The online dictionary learning algorithm [23, 24] is then employed to construct the updated dictionary, aiming to achieve sparse coefficients of hand kinematic data. Additionally, L1-norm minimization [25, 26] is utilized to address the sparse representation with the online dictionary, which can enhance performance for conducting the updated dictionary, as shown in the following problem:

$$\min_{D \in C} \lim_{n \to +\infty} \frac{1}{n} \sum_{i=1}^{n} \left(\frac{1}{2} ||x_i - D\alpha_i||_2^2 + \lambda ||\alpha_i||_1 \right) \tag{1}$$

Here, given $x_i = [x_1, \ldots, x_n] \in \mathbb{R}^{m \times n}$ is training set of signal. $D \in \mathbb{R}^{m \times p}$ is the dictionary, depending on the size of the input parameters. λ is sparsity regularizer (small positive constant), $\alpha = [\alpha_1, \ldots, \alpha_n] \in \mathbb{R}^{k \times n}$ are the coefficients of the sparse decomposition, and C is a constraint set of dictionary verifying following constraint:

$$C \triangleq \left\{ D \in \mathbb{R}^{m \times k} \text{ s.t. } \forall j = 1, \ldots, k,\ d_j^T d_j \leq 1 \right\} \tag{2}$$

Note that in the case of overcomplete dictionary, the size of dictionary $k > n$ is allowed. The updated dictionary is employed by using the sparse decomposition technique, which implements the Least Angle Regression (LARS) algorithm [25, 26]. This approach enhances the effectiveness of solving the Lasso problem and finds the sparsity, treating it as a regularization [27, 28]:

$$\min_{D \in \mathbb{R}^p} \frac{1}{2} ||x - D\alpha||_2^2 + \lambda ||\alpha||_1 + \frac{\lambda_2}{2} ||\alpha_i||_2^2 \tag{3}$$

3.3. **Principal Component Analysis (PCA).** PCA is a feature extraction technique based on dimension reduction for converting the data into a narrower features vector that still maintains most of the information in the dataset by identifying essential data relationships. Thus, the outcome of PCA is to show a feature space. Based on the hand kinematics dataset, the data consists of kinematic data in time series format which can represent the data as well. In this work, the PCA method [14] utilizes a matrix factorization technique based on the Singular Values Decomposition (SVD) algorithm to determine the eigenvalue coefficients. The SVD of the data matrix was expressed as

$$Y = U \Sigma V^{\mathrm{T}} \tag{4}$$

Here, $U \in \mathbb{R}^{d \times d}$ is a diagonal matrix, $V \in \mathbb{R}^{n \times n}$ is an orthogonal matrix, and $\Sigma \in \mathbb{R}^{d \times n}$ is a pseudo-diagonal matrix. In case Σ is diagonal matrix, where $d = n$, the singular values are expressed on the main diagonal. The covariance matrix can be constructed as

$$X = YY^{\mathrm{T}} \tag{5}$$

By subtracting Y and Y^{T} to Equation (5)

$$X = U\Sigma V^{\mathrm{T}} V \Sigma^{\mathrm{T}} U^{\mathrm{T}} \tag{6}$$

$$X = U\Lambda U^{\mathrm{T}} \tag{7}$$

where $\Lambda = \Sigma\Sigma^{\mathrm{T}} \in \mathbb{R}^{d\times d}$ represents the eigenvalues coefficients, and $U \in \mathbb{R}^{d\times d}$ can be expressed as the principal components. The selection of PCA as a benchmark in this research was influenced by several factors that highlight its advantages over other feature extraction methods. PCA is chosen due to inherent linearity and well effectiveness in dimensionality reduction. PCA offers simplicity and interpretability, making it suitable for linearly data. Additionally, PCA has the ability to capture the maximum variance in the dataset while minimizing redundancy among features. Moreover, the advantages of PCA compared with Independent Component Analysis (ICA) and Wevelat Transform (WT) are illustrated in Table 3.

Table 3. Comparisons among PCA, ICA, and WT

Feature extraction methods	**PCA**	**ICA**	**WT**
Linearity of data	Yes	Yes	No
Interpretation	Easy	Harder	Moderate
Dimensionality reduction	Yes	Yes	Yes
Data assumption	Fewest	Most	Specific (frequencies)
Computational efficiency	High	Moderate	Moderate

3.4. **Neural network classifier.** The features matrix of hand kinematic data, including 2 trials of 6 participants with 21 objects, is trained through a neural network classifier using "fitcnet" function in MATLAB software. The labeling is conducted by specifying each participant within 2 trials and 21 objects in vector format. The feature coefficients and labeling are trained with a feedforward neural network for the classifier. The first fully connected layer of the model connects to the predictor data, which refers to the train data set, and each sublayer connects to the previous layer. Each layer multiplies the input by a weight matrix and then adds a bias vector. Moreover, a Rectified Linear Unit (ReLU) is utilized for the activation function. The Limited-memory Broyden Fletcher Goldfarb Shano algorithm (LBFGS) is utilized as a parameter estimation solver. In the last layer, the Softmax function is applied as an activation function to construct the output as classification score and predicted labels. All of the hyperparameters applied for the proposed method are summarized in Table 4, and the neural network structure is illustrated in Figure 4.

Table 4. Hyperparameters for neural network classification

Hyperparameters	**Value**
Layer size	10
Costs function	Cross-entropy
Activation function	Reified Linear Units (ReLU)
Output classifier	Softmax function
Parameter estimation solver	Limited-memory Broyden Fletcher Goldfarb Shano algorithm (LBFGS)
Regularization parameter (lambda)	0

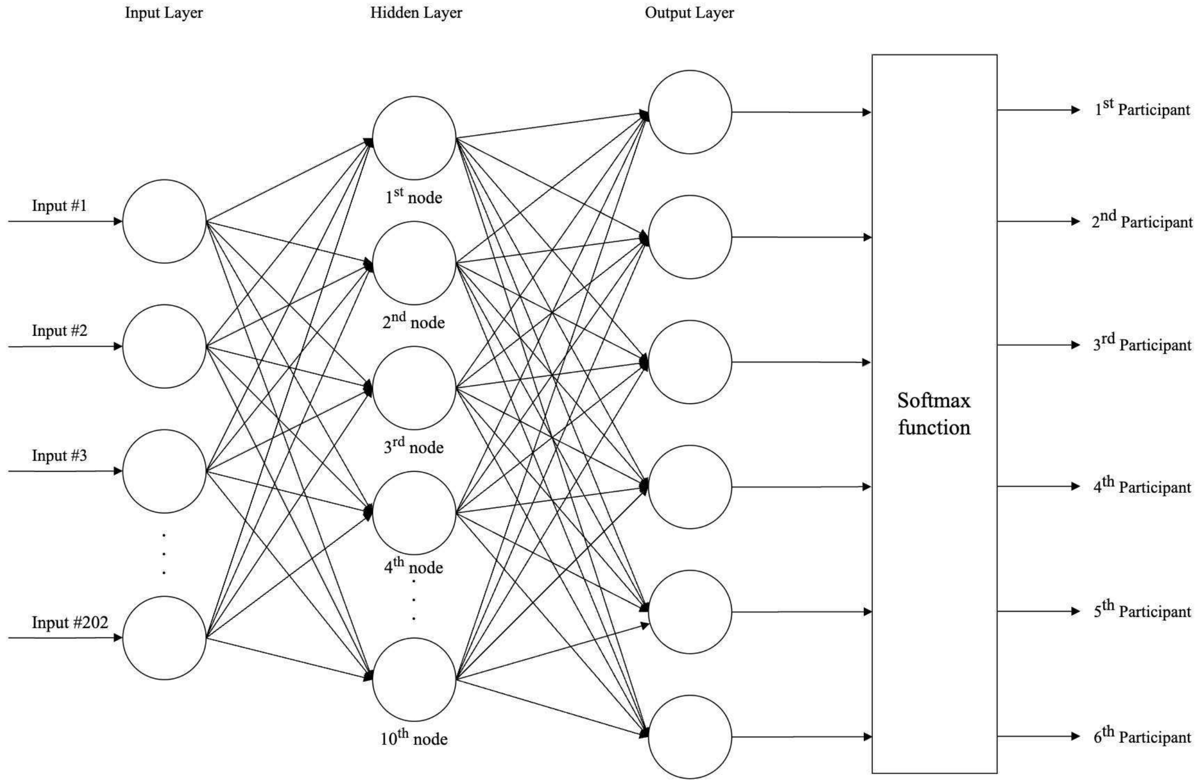


FIGURE 4. Neural network structure of the proposed method

4. **Experiments and Results.** In order to evaluate the performance of the proposed feature extraction method, the hand kinematic dataset (UNIPI dataset) has been utilized. The dataset contains 21 objects of 2 trials each, consisting of 6 participants, and the kinematic dataset was recorded based on a time series format. The labeling data is constructed following the description to label each participant within 21 objects and 2 trials in vector format. The proposed methodology consists of four major steps, which include data preprocessing, feature extraction, training the classifier, and evaluating the classifier, as shown in Figure 5. Firstly, data preprocessing techniques are employed to effectively format the kinematic data into a suitable time series format, which includes resampling and flattening processes. The second step involves the feature extraction process, where the proposed technique utilizes sparse coding for feature extraction based on dictionary learning to extract features from the hand kinematic data, providing a sparse representation. Additionally, the PCA technique is used to compare the efficiency of each feature extraction technique. The extracted feature data are used to train the classifier model in the training classifier step. The final step involves evaluating the classifier to identify participants based on the hand kinematic data, which has undergone the proposed feature extraction process and PCA technique. The proposed method implemented the sparse coding technique based on online dictionary learning into the feature extraction process as illustrated in Figure 6. The simulation is performed on MacBook Pro (14-inch, 2021) with macOS, Apple M1 Pro 8-core CPU, and 16GB unified memory in MATLAB2022b. The dictionary learning function [23, 24] is used to update the dictionary which is of size $30 \times 10{,}000$. The sparse coefficients are computed using sparse decomposition toolbox [23] which is implemented based on the LARS algorithm to improve the effectiveness of solving the Lasso problem and speed up the process. The neural network classification

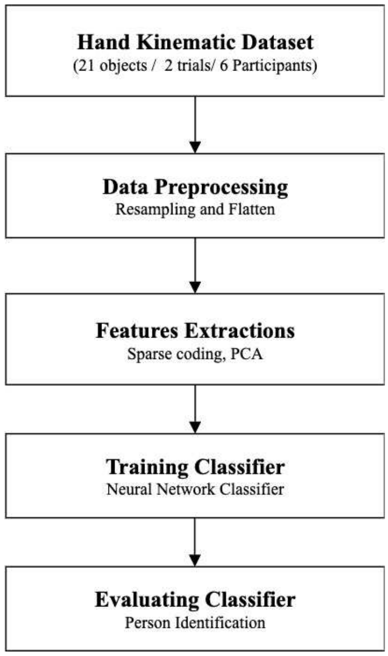


FIGURE 5. Flowchart of research methodology

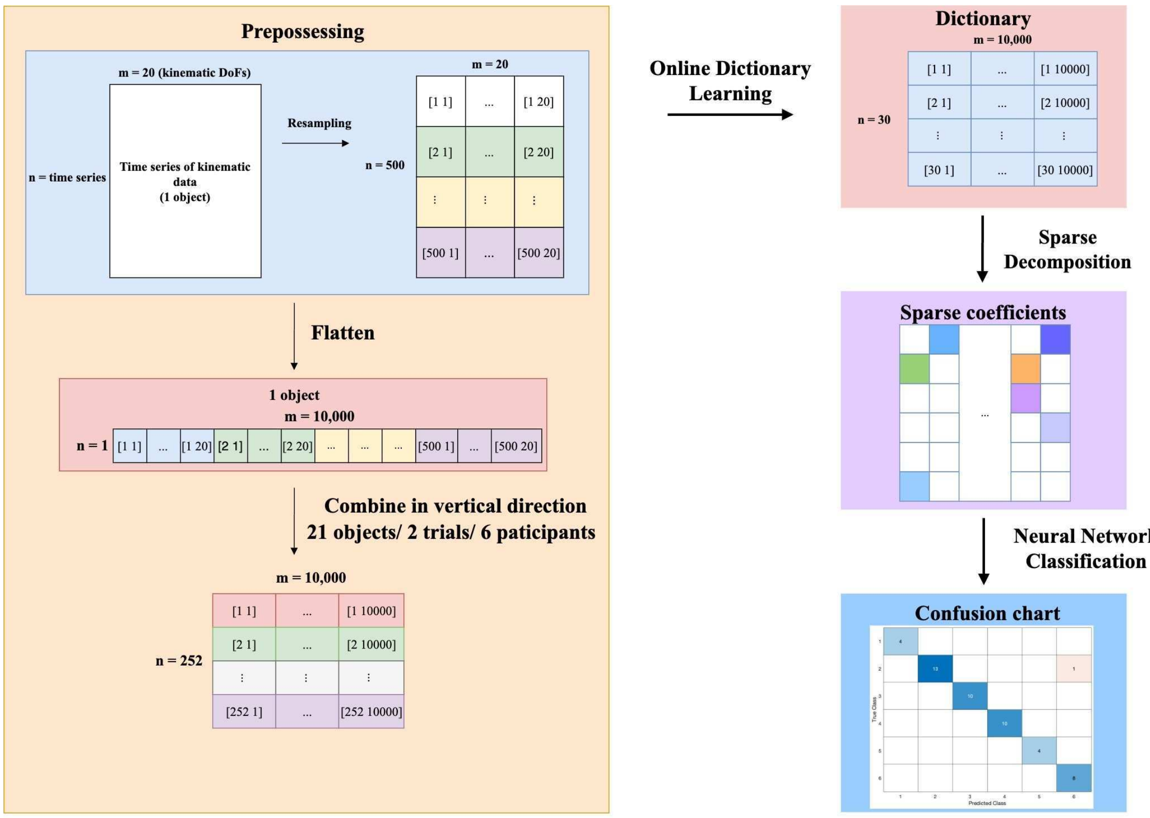


FIGURE 6. Flowchart of the proposed method

toolbox is utilized to evaluate the performance of the proposed technique and comparing with the PCA technique. The kinematic data are split into training data sets and reserved data sets for validating human identification. The training data set relatively reserved 80 percent and the reserved data set approximately reserved 20 percent of the kinematic data. To compare the proposed method with PCA, the classification metrics of three scenarios, including raw data (no feature extraction), PCA, and the proposed method, obtained using the NN classification approach, are illustrated in Table 5. The proposed method exhibited significantly improved classification accuracy of 98.00%, outperforming both the PCA technique (14.00% accuracy) and the method without feature extraction (86.00% accuracy). The average precision, recall, and F1-score of the proposed method were also notably higher compared to PCA and the method without feature extraction. Specifically, the average precision of the proposed method was 96.67%, the recall was 98.33%, and the F1-score was 97.27%. In contrast, PCA achieved an average precision of 11.67%, recall of 11.19%, and F1-score of 10.85%. Moreover, the method without feature extraction achieved an average precision of 87.40%, recall of 82.08%, and F1-score of 83.08%. Additionally, we compared the number of features among the three scenarios: raw data (no feature extraction), PCA, and the proposed method. The proposed method effectively reduced the number of features more than the PCA technique, as demonstrated in Table 6.

Table 5. Comparative analysis of classification metrics: Raw data (no feature extraction), PCA, and proposed method, utilizing neural network classification

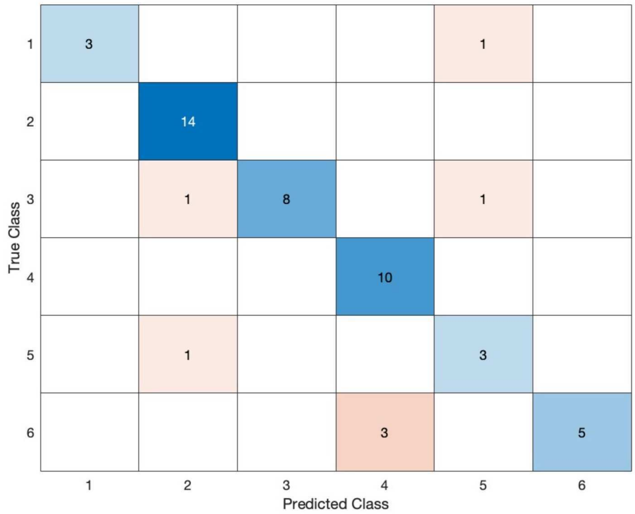
Methods	**Accuracy (%)**	**Average precision (%)**	**Average recall (%)**	**Average F1-score (%)**
Raw data	86.00	87.40	82.08	83.08
PCA	14.00	11.67	11.19	10.85
Sparse coding	**98.00**	**96.67**	**98.33**	**97.27**

Table 6. Numbers of features in a comparative analysis between scenarios with no feature extraction, PCA, and the proposed method, utilizing neural network classification

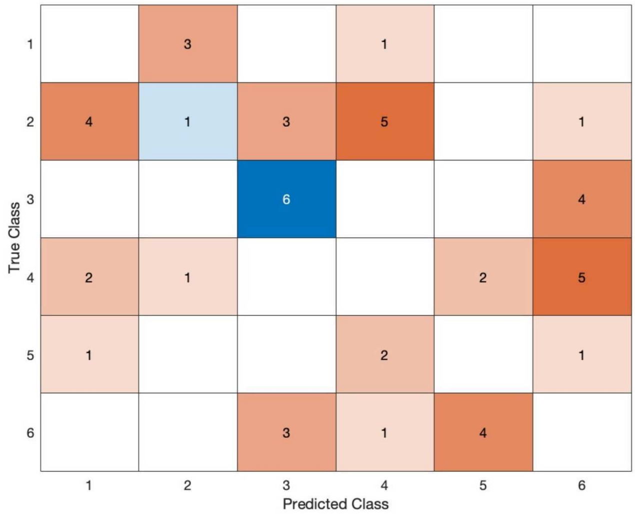
Methods	**Numbers of features**
Raw data	30,000
PCA	6,060
Sparse coding	**5,048**

5. Conclusion and Future Scope.

In the present paper, we have proposed an innovative feature extraction technique for person identification based on hand kinematic data in time series format, employing the dictionary learning technique. The proposed technique of dictionary feature extraction has been evaluated against the PCA technique on the same dataset. These approaches have been passed through the neural network classifier for human identification based on hand kinematic time series. The proposed technique outperforms PCA technique and gives high accuracy for human identification. The proposed system is currently only evaluated against the PCA technique and only the NN classifier can be further extended by utilizing other feature extraction techniques such as Independent Component Analysis (ICA). Moreover, the paper can be further improved by using other classifiers such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression for comparing performance after feature extraction processes. Finally, the proposed technique can be improved by constructing the initial dictionary with Fourier and wavelet coefficients which can be studied for improving the accuracy and speed up processing time.



(a)



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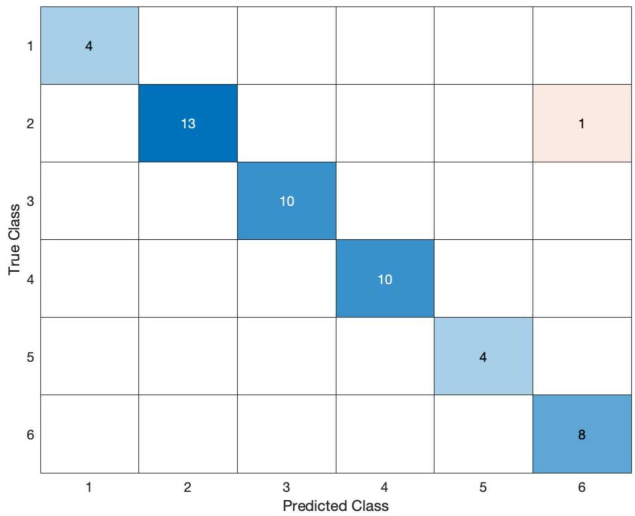

(c)

FIGURE 7. Confusion chart of comparative analysis between no feature extraction, PCA, and the proposed method based on neural network classification

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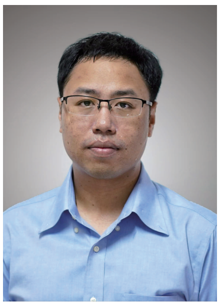
Author Biography

Jirayu Samkunta received the B.Eng. degree in Automotive Engineering from the Thai-Nichi Institute of Technology (TNI), in 2016, and the M.Eng. degree with graduate scholarship program for Excellent Thai Students (ETS) on Information and Communication Technology for Embedded Systems (ICTES) under Thailand Advanced Institute of Science and Technology – Tokyo Institute of Technology (TAIST – Tokyo Tech) Program, Sirindhorn Internation Institute of Technology (SIIT), Thammasat University (TU), Thailand in 2020. He is currently pursuing the Ph.D. degree in Graduate School of Science and Technology under Japanese Government (MEXT) Scholarships, Gunma University. In 2019, he joined the Center of Excellent in Intelligent Systems Integration at TNI. From 2020 to 2021, he joined the Digital Government Development Agency (Public Organization) as research and development specialist. His current research interests include sparse representation, dictionary learning, feature extraction, kinematic models, classification and recognition, machine learning, and artificial intelligence.



Patinya Ketthong received the B.Eng. degree in Computer Engineering from Thai-Nichi Institute of Technology (TNI), and the M.Eng. degree in Information and Communication Technology for Embedded Systems at Sirindhorn International Institute of Technology (SIIT), Thammasat University (TU), Thailand. He is currently pursuing the Ph.D. degree in Graduate School of Science and Technology, Gunma University, Japan. In 2018, he joined the Center of Excellent in Intelligent Systems Integration at TNI and is currently a lecturer and researcher at TNI. In 2016, he won the Best Paper Award from the Management and Innovation Technology International Conference, Thailand. He has published articles related to chaotic circuits and systems. His research interests include chaotic circuits and systems, chaos-based secure communications, sparse modeling, system identification and IoT systems.

Nghia Thi Mai received the B.S., M.S. and Dr. Eng. degrees from Gunma University, Gunma, Japan in 2009, 2011 and 2014, respectively. From 2014 to 2015, she was with the Human Resources Cultivation Center, Gunma University, Gunma, Japan as a research associate. From 2015 to 2021, she worked on research on damping control for automobiles at Exedy Co., Ltd. Since 2022, she has been working as a lecturer at the Department of Electrical and Electronic 1, Posts and Telecommunications Institute of Technology (PTIT). In addition, she is currently working as a visiting associate professor and part-time lecturer at the Department of Electronics and Mechanical Engineering, Gunma University. Her research interest includes Smith predictor, internal model control and robotics.

Kotaro Hashikura received the B.S. degree of Mechanical Engineering, the M.S. degree of Informatics, and the Dr. degree of Engineering from Kyushu Institute of Technology, Fukuoka, Japan in 2006, from Kyoto University, Kyoto, Japan in 2010, and from Tokyo Metropolitan University, Tokyo, Japan in 2014, respectively. From 2014 until 2018, he had been a project research associate at the Faculty of System Design, Tokyo Metropolitan University. He is currently an assistant professor at the Graduate School of Science and Technology, Gunma University, Japan. His research interests include time-delay-related control techniques, such as deadbeat, preview-prediction and repetitive controls. He is a member of IEEE, ISCIE and SICE.

Md Abdus Samad Kamal received the B.Sc. degree in Electrical and Electronic Engineering from Khulna University of Engineering and Technology (KUET), Khulna, Bangladesh in 1997, Master and Doctor degrees from Kyushu University from Graduate School of Information Science and Electrical Engineering, Japan in 2003 and 2006, respectively. He was a post-doctoral fellow in Kyushu University till November 2006. He is currently an associate professor at the Graduate School of Science and Technology, Gunma University, Japan. His current research interests include reinforcement learning, intelligent transportation systems, and multiagent systems. He is a member of IEEE and SICE.

Iwanori Murakami received the B.E., M.E. and Dr. Eng. degrees from Gunma University, Kiryu City, Japan, in 1992, 1994 and 1997, respectively. He is currently an associate professor at Gunma University. His research interests include robotics, applied electromagnetics and machines, and superconducting levitation applications.

Kou Yamada received B.S. and M.S. degrees from Yamagata University, Yamagata, Japan in 1987 and 1989, respectively, and a Dr. Eng. degree from Osaka University, Osaka, Japan in 1997. From 1991 to 2000, he was with the Department of Electrical and Information Engineering, Yamagata University, Yamagata, Japan as a research associate. From 2000 to 2008, he was an associate professor in the Department of Mechanical System Engineering, Gunma University, Gunma, Japan. Since 2008, he has been a professor in the Division of Mechanical Science and Technology, Gunma University, Gunma, Japan. His research interests include robust control, repetitive control, process control, and control theory for inverse systems and infinite-dimensional systems. Dr. Yamada received the 2005 Yokoyama Award in Science and Technology, the 2005 Electrical Engineering/Electronics, Computer, Telecommunication, and Information Technology International Conference (ECTI-CON2005) Best Paper Award, the Japanese Ergonomics Society Encouragement Award for an Academic Paper in 2007, the 2008 Electrical Engineering/Electronics, Computer, Telecommunication, Information Technology International Conference (ECTI-CON2008) Best Paper Award, and the 4th International Conference on Innovative Computing, Information and Control Best Paper Award in 2009, the 14th International Conference on Innovative Computing, Information and Control Best Paper Award in 2019, Outstanding Achievement Award from Kanto Branch of Japanese Society for Engineering Education in 2022 and JSME (The Japan Society of Mechanical Engineers) Education Award in 2023. He is a member of IEEE and SICE, and a fellow of JSME.