Gmail

Tatsanee Chaiya <tatsaneech@gmail.com>

[ICSEC 2025] Decision on your paper 1571201118 (A Mathematical Framework for Quality Assessment of Body Segment Movements Using Wishart Models)

1 message

icsec2025@gmail.com <icsec2025=gmail.com@edas.info> Tue, Sep 30, 2025 at 12:04 AM
Reply-To: icsec2025@gmail.com
To: Tatsanee Chaiya <tatsaneech@gmail.com>, Payungsak Kasemsumran <payungsak2517@gmail.com>
Cc: icsec2025@gmail.com

Dear Tatsanee Chaiya,

Congratulations! We are delighted to inform you that your manuscript ID: 1571201118 entitled 'A Mathematical Framework for Quality Assessment of Body Segment Movements Using Wishart Models' has been ACCEPTED for presentation at ICSEC 2025. All papers presented at ICSEC 2025 will be published in IEEE Xplore.

We will send more detail for the instructions later.

Best regards,

ICSEC 2025 General Chair

Reviewers' comments:

======= ICSEC 2025 1 =======

> *** Content: Does it reflect excellence of research work; is the paper technically sound?
Good (4)

> *** Originality: Provides a novel approach, does the paper discuss new/unpublished work?
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> *** Relevance: How well does the content fit the conference topics?
Somewhat relevant (2)

> *** Clarity: Does the paper clearly communicate its message?
Fair (3)

> *** Reviewer's Confidence: How familiar is the reviewer with the topic?
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> *** Overall Recommendation: Choose from:
Accept (4)

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1. applying Wishart distribution to covariance matrices and measure the similarity by different entropy measures is appropriate.
2. There is no detail of parameters, number of frames, size of each frame in the experiement. The authors must address this detail in the paper before the final acceptance.
3. Explain why only KL divergence was reported. The authors should report other rmeasures as well (se Section 2.5) and discuss the result from each measure.

======= ICSEC 2025 2 =======

> *** Content: Does it reflect excellence of research work; is the paper technically sound?
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> *** Originality: Provides a novel approach, does the paper discuss new/unpublished work?
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> *** Relevance: How well does the content fit the conference topics?
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> *** Clarity: Does the paper clearly communicate its message?
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> *** Reviewer's Confidence: How familiar is the reviewer with the topic?
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This paper introduces a novel, computationally efficient framework for real-time movement assessment using Wishart models, demonstrating strong results on public datasets. Its main weakness is the simplicity of features used. Future work could explore incorporating more informative features to further improve discriminative power.

======= ICSEC 2025 3 =======

> *** Content: Does it reflect excellence of research work; is the paper technically sound?
Excellent (5)

> *** Originality: Provides a novel approach, does the paper discuss new/unpublished work?
Excellent (5)

> *** Relevance: How well does the content fit the conference topics?
Relevant (3)

> *** Clarity: Does the paper clearly communicate its message?
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Strong Accept (5)

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The framework assumes that joint-level features are independent samples from a multivariate normal distribution, which justifies the use of Wishart distributions. In practice, human joint trajectories may deviate from Gaussianity due to biomechanical constraints or sensor noise. Please discuss the robustness of your model to such deviations and whether extensions (e.g., elliptical distributions or robust covariance estimators) might improve generalization.

The model builds covariance matrices per joint (3×3), which ensures SPD structure and avoids singularity. However, this ignores correlations across joints within the same segment. A discussion on the trade-off between computational effici.

Agenda (November 4, 2025) 9.00 -12.00

Chair:

Room 3(Doi Nua): Data Science; Machine Learning and Intelligent Systems , Network (10.40 - 12.00)

No.	Time Start	Time End	Paper ID	Title	Author
77	10:40	11:00	1571155330	M-BurnScar: Temporal-Based Burnt Scar Profiling for Modelling Risk of Forest Fires in ASEAN Countries	Surapol Vorapatratorn
78	11:00	11:20	1571197956	On the Performance of Offloading Robustness for UAV-Mounted RIS with NOMA-Aided MEC	Gia-Huy Nguyen
79	11:20	11:40	1571197964	UAV-Based MEC in RSMA-Assisted AmBC Networks: Outage Offloading and System Throughput	Gia-Huy Nguyen
80	11:40	12:00	1571201118	A Mathematical Framework for Quality Assessment of Body Segment Movements Using Wishart Models	Tatsanee Chaiya
	12:00	13:00		Lunch	

Chair:

Room 4(Doi Suthep 1): AI in Healthcare 1 (9.00 - 12.00)

No.	Time Start	Time End	Paper ID	Title	Author
81	9:00	9:15	1571200032	STN-MRI: A Spatial Transformer Network-Based Pipeline for ROI-Aware Brain MRI Preprocessing and Alignment	Vyshnavi Ramineni
82	9:15	9:30	1571177643	BERT-FastText and BERT-BiLSTM Fusion for Chinese Hate Speech Detection	Methini Ma
83	9:30	9:45	1571176155	Language-Agnostic Framework for MCI Detection Using Whisper-Based Acoustic Features	Nyi Nyein Aung
84	9:45	10:20	1571196355	Deep Learning for Non-Contact Anthropometry from RGB-D Data in Extreme Environments	Jaehee Hong
85	10:00	10:15	1571190953	Empowering Clinical Outcomes with AI Powered Innovations in Medical Imaging Diagnostics	Abdoh Jabbari
	10:15	**10:30**		**Coffee Break**	
86	10:30	10:45	1571159198	Machine Learning-Driven Prediction and Analysis of Mental Health Risks Among University Students	Soontarin Nupap
87	10:45	11:00	1571197758	Comparative Study of Deep Neural and Kolmogorov-Arnold Networks for Heart Disease Risk Stratification via Stethoscopic Signals	Nawat Suangburanakul
88	11:00	11:15	1571174995	Integrating Pseudo-Relevance Feedback with Deep Learning for Automated ICD-10 Coding	Kitti Akkhawatthanakun
89	11:15	11:30	1571200462	Neuropeptide Classification at Scale with Protein Language Models: Hard Negatives and Cluster-Aware Splits	Wachirawit Intaphan
90	11:30	11:45	1571199610	AI-Driven Longitudinal Modeling of APOE Genotype and Hippocampal Atrophy in Alzheimer's Disease Cognitive Decline	Faizaan Khan

A Mathematical Framework for Quality Assessment of Body Segment Movements using Wishart Models

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Abstract— **Automated movement quality assessments enable effective physical therapy by allowing real-time detection of improper movements. While previous methods primarily offer offline, full-body evaluations, this paper presents a novel framework for online human motion modelling and accuracy assessment. Our approach uses covariance matrices to capture full-body motion, with the capability to focus on individual body segments. These matrices are computed continuously during a correct exercising movement and used to create an exemplar Wishart model to characterize dynamic motion of the correct movements. For a query sample performing the same exercise, a second set of Wishart models is generated using online density estimation. We then compare these distributions to the exemplar's in real-time, using a dissimilarity metric to quantify deviations. This allows the framework to identify incorrect movements and pinpoint specific body segments contributing to poor performance. Experiments on three public datasets demonstrate that our framework achieves an average AUC-ROC score of 95.2% for full-body quality assessment. It effectively detects real-time movement errors and distinguishes varying levels of deviation for each body segment.**

Keywords—Wishart distribution, Covariance matrix, Body segment movements, Human motion assessment.

I. INTRODUCTION

Therapeutic exercises are vital for patients in physical rehabilitation to improve joint and muscle function. Each year, about 24 million exercise sessions are conducted, with over 90% performed at home [1]. While physiotherapists periodically monitor progress, many patients cannot afford daily professional supervision, leading to poor adherence to treatment plans, slower recovery, and potentially higher healthcare costs.

This paper introduces a novel framework to help the patients evaluate the accuracy of physical movements. By modeling body motion and providing immediate feedback during exercise, our framework conducts real-time analysis to detect incorrect movements, identifying specific body segments that deviate from proper motion. This scalable approach is suitable for customized home-based applications.

Covariance descriptors have proven effective in capturing low-level features for human action recognition and motion analysis. In [2], covariance matrices were constructed over time series of 3D joint positions for hand gesture recognition, using the Log-Euclidean metric with a k-Nearest Neighbor classifier. The authors of [3] introduced temporal hierarchical covariance descriptors for action recognition, constructing matrices from overlapping windows of feature vectors to capture the temporal order of 3D joint positions. In [4], hierarchical covariance descriptors using kinematic features were classified with a modified Log-Euclidean metric for multiple kernel learning. In a related work, [5] built hierarchical covariance matrices using the most informative joint features. Recently, [6] applied hierarchical covariance descriptors to model the dynamics of body parts, significantly improving classification accuracy in action recognition.

Despite these advancements, none of these studies explored the use of covariance descriptors for evaluating movement quality. Only a few, such as [7] and [8], have adopted Wishart distributions of covariance descriptors for human motion analysis. Moreover, previous studies often relied on high-dimensional movement data to construct covariance matrices, which are computationally inefficient for real-time applications. Geodesic metrics like Affine-Invariant, Log-Euclidean, Stein, and Cholesky distances are designed for symmetric positive definite (SPD) matrices, which require full rank to remain positive definite. When the data dimension exceeds the number of samples, the covariance matrix becomes singular, making these metrics unsuitable for similarity measurements. In contrast, this paper constructs covariance matrices using only three-dimensional features, ensuring they remain SPD and efficient for real-time applications.

Recently, machine learning and deep learning algorithms have been extensively applied to human motion assessment. Earlier approaches utilized methods like HMM, GMM, and SVM to evaluate motions for both full-body and specific body parts [9] - [12]. Studies also compared the performance of RF, KNN, SVM, and MLP for tasks like fall detection. More recently, deep learning models such as GAN, CNN, LSTM, GRU, GCN, and Res-TCN have been employed to assess human motions using skeleton data and RGB images [13] - [15], and [22] - [26]. However, these models often require a large number of skeleton sequences or RGB images for training. For example, in [26], while their deep learning models (LSTM, BiLSTM, CNN, and CNN-LSTM) achieved high classification accuracies of 95%–98%, the training process took 2.15 to 13.45 minutes and demanded a substantial number of training samples to build robust classifiers.

In contrast, our proposed framework constructs exemplar models with discriminating power comparable to previous research while using only one or a few motion sequences. This approach significantly reduces the reliance on extensive training samples and computational resources, making it both efficient and practical. Additionally, unlike

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C. Covariance Descriptor

The covariance descriptors are constructed based on the authors' previous proposed method [8]. A covariance descriptor of a single joint is represented as

$$\boldsymbol{C}_j = \frac{1}{T-1}\boldsymbol{F}_j\boldsymbol{F}_j' \qquad (2)$$

A set of covariance matrices, denoted as $\{\boldsymbol{C}_j | j \in \{1, \dots, J\}\}$, are constructed using the feature matrix defined in Equation 1. The set of covariance matrices are used to characterize movements of all joints, where $\boldsymbol{C}_j \in \mathbb{R}^{3\times 3}$ is a sample covariance matrix for the j^{th} joint.

2.3.1 Full-body covariance descriptors: all J covariance matrices are used to capture motion information of the full body. For building an exemplar model, a set of covariance matrices $\{\boldsymbol{C}_{1,j} | j \in \{1, \dots, J\}\}$ are constructed using all T_1 frames to characterize the exemplar's movement repetitions. For building a test sample, a set of $\{\boldsymbol{C}_{2,j} | j \in \{1, \dots, J\}\}$ covariance matrices are re-computed as the number of frames increments over time.

2.3.2 Body-segment covariance descriptors: body joints are decomposed into five body segments as shown in TABLE . Hence, a subset of six covariance matrices $\{\boldsymbol{C}_j | j \in J_{torso}\}$ is used to characterize motion in torso. Other subsets of four covariance matrices: $\{\boldsymbol{C}_j | j \in J_{leftArm}\}$, $\{\boldsymbol{C}_j | j \in J_{rightArm}\}$, $\{\boldsymbol{C}_j | j \in J_{leftLeg}\}$, and $\{\boldsymbol{C}_j | j \in J_{rightLeg}\}$ are used to characterize motions in left/right arms and left/right legs, respectively.

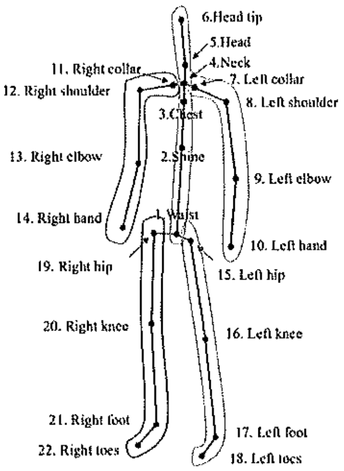

Fig. 2. Skeleton joints from a Kinect v2 motion sensor are grouped into five body segments.

D. Wishart Models

The feature vectors $\boldsymbol{f}_j^{(t)}$ are assumed independent random samples and are drawn from a multivariate normal distribution $\mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$. Consequently, the covariance descriptors, defined in Equation 2, are symmetric positive definite matrices, and each of them follows a Wishart distribution $\boldsymbol{C}_j \sim \mathcal{W}_d(n, \boldsymbol{\Sigma})$. The probability density function of a Wishart distribution with $n \in \mathbb{R}$ degree of freedom and a scale matrix $\boldsymbol{\Sigma} \in \mathbb{R}^{\mathrm{d}\times\mathrm{d}}$ is [16]:

$$\mathcal{W}_d(\boldsymbol{C}_j; n, \boldsymbol{\Sigma}) = \frac{|\boldsymbol{C}_j|^{\frac{n-d-1}{2}}}{2^{\frac{nd}{2}}|\boldsymbol{\Sigma}|^{\frac{n}{2}}\Gamma_{\mathrm{d}}\left(\frac{\mathrm{n}}{2}\right)}\exp\left\{-\frac{1}{2}tr(\boldsymbol{\Sigma}^{-1}\boldsymbol{C}_j)\right\}$$

where $\Gamma_{\mathrm{d}}(\alpha) = \pi^{\frac{d(d-1)}{2}}\prod_{i=1}^{d}\Gamma\left(\alpha - \frac{i-1}{2}\right)$ is a multivariate gamma function, $\Gamma(\cdot)$ is a gamma function, and $tr(\cdot)$ is a trace operator.

To obtain the maximum likelihood estimates $\hat{n}$ and $\hat{\boldsymbol{\Sigma}}$ for the Wishart parameters, we modified the algorithm proposed in [17] as outlined in Algorithm 1. If $\theta_n = ((n-d-1)/2)$, $\theta_{\boldsymbol{\Sigma}} = \boldsymbol{\Sigma}^{-1}$, and M is the total number of joints in a body segment, the objective function for this iterative method is expressed as follows:

$$\begin{aligned} E(\theta_n, \theta_{\boldsymbol{\Sigma}}) = &\left(\theta_n + \frac{d+1}{2}\right)(d\log 2 - \log|\theta_{\boldsymbol{\Sigma}}|) \\ &+ \log\Gamma_d\left(\theta_n + \frac{d+1}{2}\right) \\ &- \langle\frac{1}{M}\sum_{j=1}^{M}\left(\log|\boldsymbol{C}_j|, -\frac{1}{2}\boldsymbol{C}_j\right), (\theta_n, \theta_{\boldsymbol{\Sigma}})\rangle \end{aligned}$$

- *Building Wishart models for exemplar samples:* If K motion sequences are selected as exemplar samples, a set of $K \times J$ covariance matrices, denoted as $\{\boldsymbol{C}_j^{(k)} | j \in \{1, 2, \dots, J\}, k \in \{1, \dots, K\}\}$, are constructed. Hence, five subsets of the constructed covariances matrices: $\{\boldsymbol{C}_j^{(k)} | j \in J_{torso}\}$, $\{\boldsymbol{C}_j^{(k)} | j \in J_{leftArm}\}$, $\{\boldsymbol{C}_j^{(k)} | j \in J_{rightArm}\}$, $\{\boldsymbol{C}_j^{(k)} | j \in J_{leftArm}\}$, and $\{\boldsymbol{C}_j^{(k)} | j \in J_{rightArm}\}$ are used for modelling motions of five body segments.
  A Wishart model for capturing full-body movement of an exemplar sample is denoted as $\mathcal{W}_d(n_e, \boldsymbol{\Sigma}_e)$, a set of Wishart models for capturing body segments of the exemplar sample is denoted as $\left\{\mathcal{W}_d\left(n_e^{(p)}, \boldsymbol{\Sigma}_e^{(\mathrm{p})}\right) | p\{1, \dots, 5\}\right\}$.
- *Building Wishart models for test samples:* Both full-body and body-segment covariance matrices are built in the same manner as for the exemplar sample. We denote $\mathcal{W}_d(n_s, \boldsymbol{\Sigma}_s)$ as a Wishart model for capturing full-body movement of a test sample and $\left\{\mathcal{W}_d\left(n_s^{(p)}, \boldsymbol{\Sigma}_s^{(\mathrm{p})}\right) | p \in \{1, \dots, 5\}\right\}$ as a set of Wishart models for capturing body segments of the test sample.

While the exemplar Wishart models are computed once (offline), the test Wishart models are updated with each new frame entering data stream (online). At each time step t, six pairs of Wishart models are used to assess the movement quality of the test sample. For instance, we measure the dissimilarity between $\mathcal{W}_d\left(n_e^{(1)}, \boldsymbol{\Sigma}_e^{(1)}\right)$ and $\mathcal{W}_d\left(n_s^{(1)}, \boldsymbol{\Sigma}_s^{(1)}\right)$ to evaluate how much the torso motion of the test sample deviates from the normal torso motion of the exemplar. The parameter estimates of these Wishart models are then used to compute dissimilarity scores, quantifying the deviation from normality.

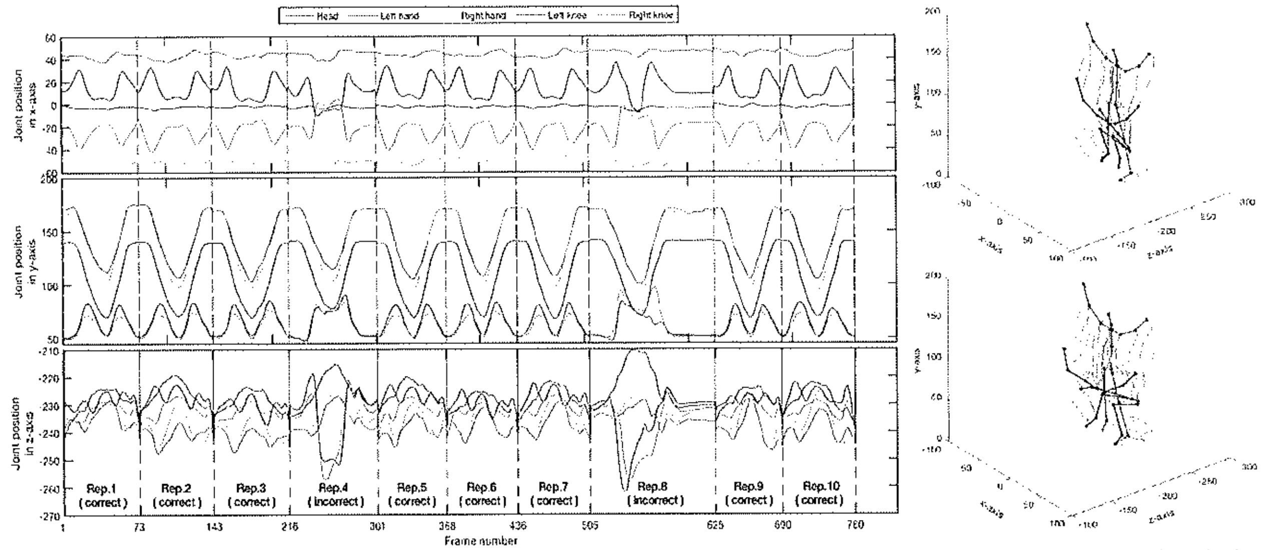

Fig. 3: Illustration of five joint positions in x-y-x coordinates of a subject performing a deep squat in UI-PRMD dataset. Illustration of joint trajectories in 3D space. Joint trajectories of a subject performing a deep squat with a correct form (top) and an incorrect form (bottom).

$$\frac{d_{t_2}(s) - d_{t_1}(s)}{\Delta t} > 0,$$

and $d_t(s)$ is a dissimilarity score of the test sample s computed at frame t, and $t_2 = t_1 + \Delta t$. While the quality label is used to detect abnormality of the test sample, the dissimilarity score determines deviations from normality in real-time.

For both offline and online movement quality assessments, dissimilarity scores and quality labels can be reported for different body parts: the full body, torso, left/right arms, and left/right legs. Thus, six exemplar Wishart models—one for the full body and one for each body part—are simultaneously built, and six distributions of dissimilarity scores are computed to establish a normality threshold for each part.

III. EXPERIMENTAL PROCEDURE

A. Datasets

The UI-PRMD [19] dataset, specifically designed for human motion analysis, was well-suited for evaluating our framework for both offline and online movement quality assessments. This dataset comprised 10 physical therapy exercises, with each subject performing 10 repetitions of each exercise in both correct (optimal) and incorrect (non-optimal) forms. This resulted in a total of 200 multiple-repetition motion sequences, equating to 2,000 individual exercise repetitions, capturing 3D joint positions and joint angles. Fig. 3 illustrates the joint trajectories in 3D space of a subject performing a deep squat. In the correct deep squatting movements (top), the subject maintained an upright upper body with knees aligned over the feet. Conversely, the incorrect deep squatting movements (bottom) featured a non-upright trunk and knee valgus collapse. Additionally, we used other public motion datasets, such as MSR-Action3D [20] and UTKinect [21], in experiments to select an appropriate similarity distance metric.

B. Data Preprocessing

Skeleton data derived from motion sensors often contain noise due to occlusions. To denoise the raw skeleton data, we applied a Savitzky-Golay smoothing filter. MATLAB's built-in *sgolayfilt* function was used for this purpose, as it not only reduced noise but also aligned delays and removed transient effects at the start and end of the data stream. Typically, raw data from motion sensors were prepared in a real-world 3D coordinate system, which varied depending on the subject's location. Additionally, differences in body sizes led to variations in coordinate scales. Therefore, raw skeleton data were often pre-processed to achieve viewpoint and body-scale invariance. To ensure these properties, we created a human coordinate system by using the subject's waist joint as the new coordinate origin. The coordinate values of other joints were then recalculated relative to this origin and normalized using the minimum and maximum joint position values.

After preprocessing, a set of 22 joint features and covariance descriptors, constructed as described in Section II, were created for each time frame for quality assessment.

TABLE II. CLASSIFICATION ACCURACIES FROM CLASSIFYING ACTIONS IN USING K-NN WITH FOUR DISTANCE METRICS.

Distance metric	UI-PRMD		MSR-Actoion3D	UTKinect
	Normal only	With abnormal		
d_{KL}	97.67%	88.60%	94.09%	87.00%
d_B	98.33%	89.05%	92.22%	85.00%
d_H	98.67%	88.20%	86.83%	79.84%
d_R	97.67%	88.70%	87.42%	85.00%

C. Selection of a Distance Metric

To assess the discriminative capability of the 3x3 Wishart models combined with the dissimilarity metrics in Equations 3 – 6 for classification, the dissimilarity score distributions for various actions within the UI-PRMD

IV. RESULTS

A. *Experiment 1: Offline Quality Assessment*

Binary classifiers described in Section 2.6 were built, each specifically designed to detect incorrect movements for a particular action. To train each classifier, 200 motion sequences for each action were split into a training set and a test set. The training set included 70 correct and 70 incorrect movement sequences, while the remaining 60 sequences (30 correct and 30 incorrect) were used for testing. From the training set, 10 correct sequences were randomly selected as exemplars to build the exemplar model. All 70 correct sequences in the training set were used to establish a distribution of dissimilarity scores and to compute the threshold defined in Equation 7. However, for experiments, we utilized the 70 incorrect sequences in the training set to search for an optimal threshold that maximized the classifier's performance.

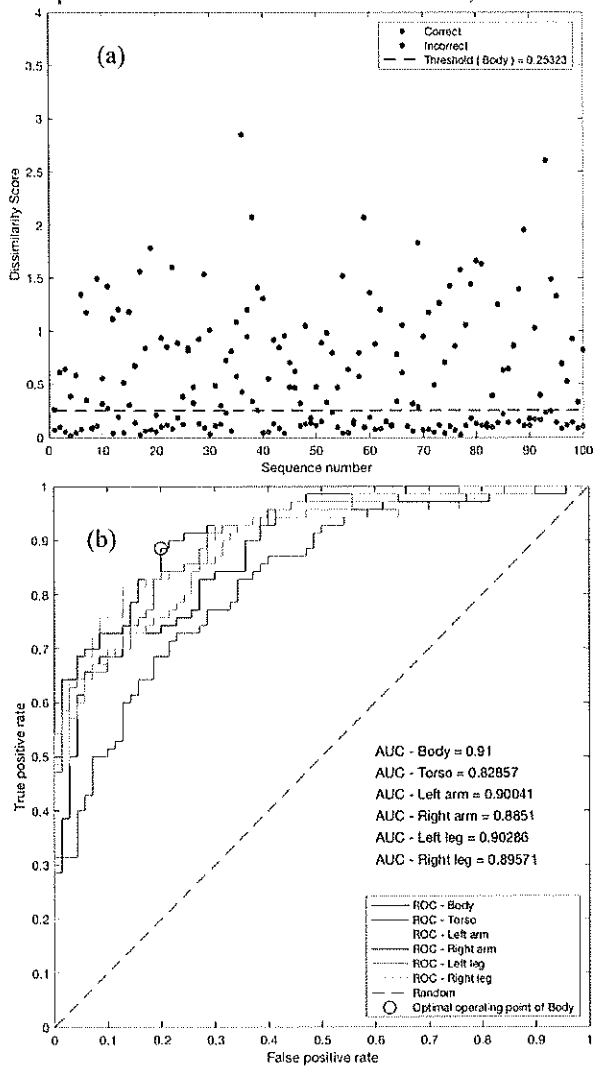

Fig. 6. Results from classification of correct and incorrect deep squatting movements showing (a) dissimilarity scores and (b) ROC curves.

Results from detecting movements of a subject performing deep squat are shown in Fig. 6. Fig. 6a visualizes the distribution of dissimilarity scores for all 200 deep-squat sequences based on full-body modelling. It can be observed that the dissimilarity scores for correct sequences (red) were typically smaller and less variable than those for incorrect ones (blue).

To detect incorrect movements for a specific action, six exemplar models were constructed to represent six body parts: the full body, torso, left/right arms, and left/right legs. After computing dissimilarity scores for the training

TABLE III. STATISTICAL RESULTS FROM CLASSIFYING CORRECT AND INCORRECT MOVEMENTS OF ACTIONS IN UI-PRMD DATASET.

Action	Body segment	Precision	Recall	Specificity	Accuracy	AUC
Deep squat	Full-body	0.96	0.93	0.97	0.95	0.91
	Torso	0.84	0.90	0.83	0.87	0.83
	Left arm	0.85	0.97	0.83	0.90	0.90
	Right arm	0.84	0.87	0.83	0.85	0.89
	Left Leg	0.82	0.93	0.80	0.87	0.90
	Right Leg	0.81	0.87	0.80	0.83	0.89
Hurdle step	Full-body	1.00	1.00	1.00	1.00	1.00
	Torso	1.00	1.00	1.00	1.00	1.00
	Left arm	0.91	1.00	0.90	0.95	0.99
	Right arm	1.00	1.00	1.00	1.00	1.00
	Left Leg	0.95	0.90	0.95	0.93	0.97
	Right Leg	1.00	1.00	1.00	1.00	1.00
Side lunge	Full-body	0.80	1.00	0.75	0.87	0.91
	Torso	0.85	1.00	0.83	0.88	0.90
	Left arm	0.87	0.93	0.88	0.87	0.90
	Right arm	0.83	0.86	0.83	0.83	0.86
	Left Leg	0.74	0.83	0.67	0.81	0.85
	Right Leg	0.77	0.96	0.71	0.83	0.81
Shoulder abduction	Full-body	1.00	0.96	1.00	0.98	0.99
	Torso	1.00	1.00	1.00	1.00	1.00
	Left arm	1.00	1.00	1.00	1.00	1.00
	Right arm	1.00	1.00	1.00	0.98	0.98
	Left Leg	1.00	1.00	1.00	0.95	0.91
	Right Leg	0.92	0.92	0.92	0.96	0.99
Shoulder scaption	Full-body	0.85	0.83	0.83	0.88	0.95
	Torso	0.96	0.96	0.96	0.96	0.99
	Left arm	0.96	0.96	0.96	0.96	0.98
	Right arm	0.85	0.92	0.83	0.88	0.92
	Left Leg	0.95	0.81	0.96	0.88	0.88
	Right Leg	0.87	0.87	0.88	0.87	0.90

TABLE IV. PERFORMANCE COMPARISON OF RELATED STUDIES IN CLASSIFYING MOVEMENT QUALITY USING UI-PRMD DATASET.

Method	Accuracy rate	F1-Score	Training Time (min.)
GCN [22]	0.92	-	-
Res-TCN (Deep squat) [23]	0.83	-	-
Res-TCN (All actions) [23]	0.62	-	-
Graph Transformer [24]	-	0.85	-
LSTM [25]	0.98	-	-
CNN-LSTM [25]	0.87	-	-
GRU [25]	0.92	-	-
Bidirectional LSTM [26]	0.95	0.94	13.45
LSTM [26]	0.98	0.98	4.18
CNN-LSTM [26]	0.98	0.98	8.54
CNN [26]	0.99	0.99	2.15

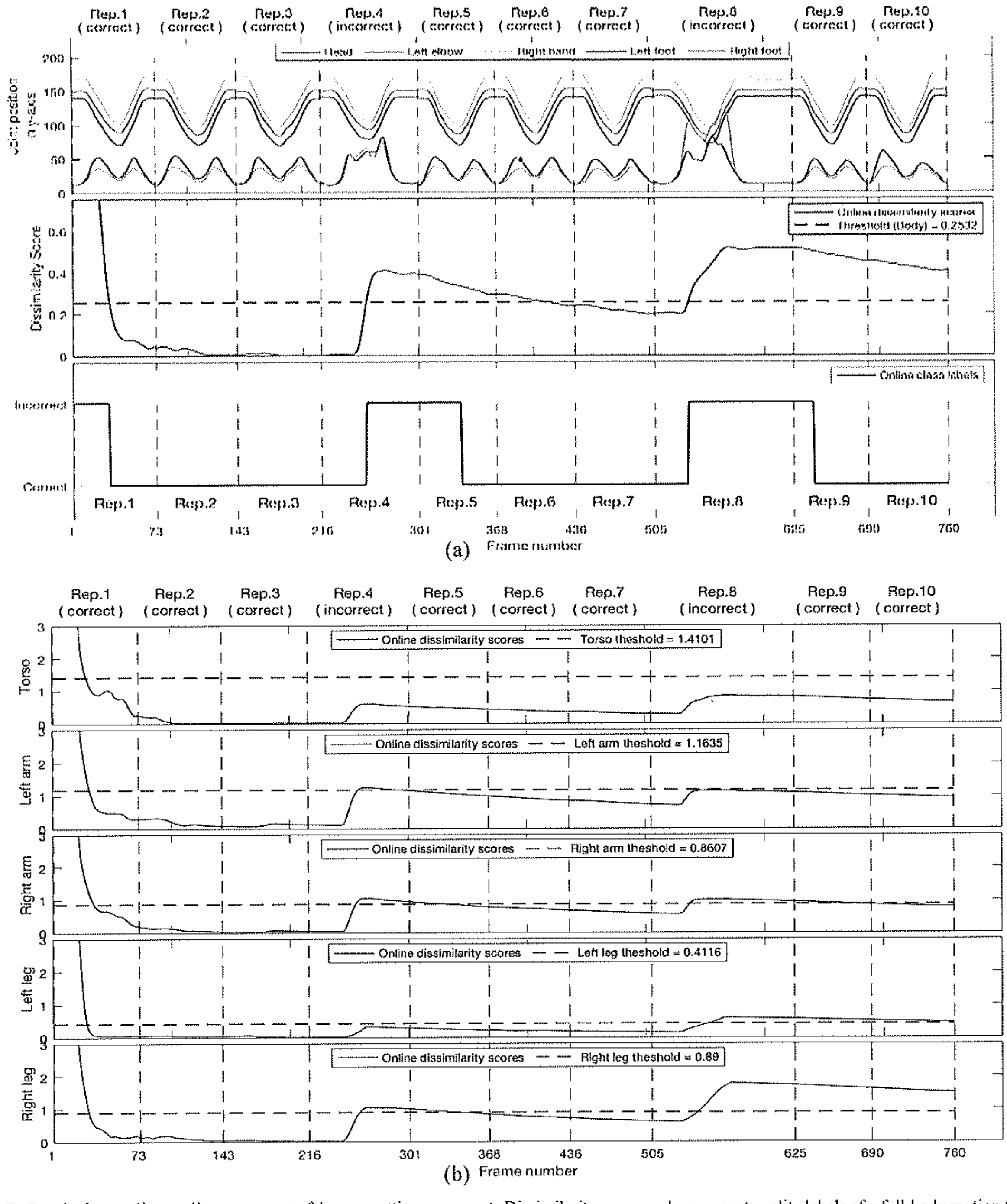

Fig. 7. Results from online quality assessment of deep-squatting movement. Dissimilarity scores and movement quality labels of a full-body motion (a) and five body segments (b).

considered for automatically extracting movement cycles or repetitions, enabling quality assessment of both periodic and non-periodic movements.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. All research work, analysis, and results presented in this study were conducted independently, without any financial, commercial, or personal relationships that could be construed as a potential conflict of interest.

REFERENCE

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มีความประสงค์จะยืมเงินจาก งานคลัง วิทยาลัยพลังงานทดแทน

เพื่อเป็นค่าใช้จ่าย ทดรองจ่ายค่าลงทะเบียนเข้าร่วมนำเสนอบทความ ดังรายละเอียดต่อไปนี้

บันทึกข้อความ ที่ อว 69.17.1/1455 ลงวันที่ 24 ตุลาคม 2568	8,000.00
(ตัวอักษร) **แปดพันบาทถ้วน** รวมเงิน(บาท)	**8,000.00**

ข้าพเจ้าสัญญาว่าจะปฏิบัติตามระเบียบของทางการทุกประการและจะนำใบสำคัญจ่ายที่ถูกต้องพร้อมทั้งเงินเหลือจ่าย(ถ้ามี) ส่งใช้ภายในกำหนดไว้ในระเบียบมหาวิทยาลัยแม่โจ้ว่าด้วยการใช้เงินรายได้เป็นเงินทดรองราชการ พ.ศ. 2546 และที่แก้ไขเพิ่มเติม ถ้าข้าพเจ้าไม่ส่งตามกำหนด ข้าพเจ้ายินยอมให้หักเงินเดือน ค่าจ้าง เบี้ยหวัด บำเหน็จ บำนาญ หรือเงินอื่นที่ข้าพเจ้าจะพึงได้รับจากทางราชการชดใช้จำนวนเงินที่ยืมไปจนครบถ้วนได้ทันที

ข้าพเจ้าขอรับรองว่า ☑ ไม่มีสัญญายืมเงินฉบับเก่าคงค้าง

☐ มีสัญญายืมเงินฉบับเก่าคงค้าง จำนวน ....ฉบับ เป็นเงิน..บาท ดังนี้

ลำดับ	เลขที่สัญญายืมเงิน	วันครบกำหนด	จำนวนเงินตามสัญญา	จำนวนเงินส่งใช้	คงเหลือ	คำชี้แจง

ลายมือชื่อ ทัศนีย์ ชัยยา ผู้ยืม วันที่

เสนอ คณบดีวิทยาลัยพลังงานทดแทน

ได้ตรวจสอบแล้ว ข้อมูลข้างต้นถูกต้องทุกประการ

ลายมือชื่อ อัญชลี เจ้าหน้าที่ผู้ตรวจสอบ ลายมือชื่อ จิราพร หัวหน้าผู้ควบคุม

(นางสาวอัญชลี สายเขียว) (นางจิราพร ดุษฎี)

ได้ตรวจสอบแล้ว เห็นสมควรอนุมัติให้ยืมตามใบยืมฉบับนี้ได้ จำนวน 8,000.00 บาท

(แปดพันบาทถ้วน)

ลายมือชื่อ วันที่

(ผศ.ดร.กิตติกร สาสุจิตต์)

รองคณบดีวิทยาลัยพลังงานทดแทนฝ่ายบริหาร

คำอนุมัติ

อนุมัติให้ยืมเงินตามเงื่อนไขข้างต้นได้ จำนวน 8,000.00 บาท (แปดพันบาทถ้วน)

ลายมือชื่อ ผู้อนุมัติ วันที่

(ผศ.ดร.นิกราน หอมดวง)

คณบดีวิทยาลัยพลังงานทดแทน

ใบรับเงิน

ได้รับเงินยืม จำนวน 8,000.00 บาท (แปดพันบาทถ้วน) ไว้เป็นการถูกต้องแล้ว

ลายมือชื่อ ทัศนีย์ ชัยยา ผู้รับเงิน วันที่

รายการส่งใช้เงินยืม

สัญญายืมเงิน เลขที่ .... ชื่อผู้ยืม น.ส.ทัศนีย์ ชัยยา .... (หน้า 2)

การส่งใช้ครั้งที่	วัน เดือน ปี	รายการส่งใช้ จำนวนเงิน		คงค้าง (บาท)	ลายมือชื่อผู้รับเงิน	ใบรับเลขที่
		เงินสด	ใบสำคัญ			

หมายเหตุ (1) ยืมต่อ ผู้อำนวยการกองคลัง หัวหน้ากอง หัวหน้าแผนก หรือตำแหน่งอื่นใดที่ปฏิบัติงานเช่นเดียวกันแล้วแต่กรณี

(2) ให้ระบุชื่อส่วนราชการที่จ่ายเงินยืม

(3) ระบุวัตถุประสงค์ที่จะนำเงินยืมไปใช้จ่าย

(4) เสนอต่อผู้มีอำนาจอนุมัติ