Journal of Computer Science

Original Research Paper

Feature Extraction of Sit-to-Stand Transition Using Vision-Based Pose Estimation

[1]Achmad Rizal, [2]Bayu Erfianto, [3]Sugondo Hadiyoso and [1]Istiqomah

[1]*School of Electrical Engineering, Telkom University, Bandung, Indonesia*
[2]*School of Computing, Telkom University, Bandung, Indonesia*
[3]*School of Applied Science, Telkom University, Bandung, Indonesia*

Article history
Received: 29-08-2024
Revised: 06-12-2024
Accepted: 18-12-2024

Corresponding Author:
Achmad Rizal
School of Electrical Engineering, Telkom University, Bandung, Indonesia
Email: achmadrizal@telkomuniversity.ac.id

Abstract: Sit-to-Stand Transition (STS) and vice versa are important indicators of independence and physical health. For normal people, this movement is easy to do but can be difficult for people who have health problems, such as those who have had an injury or stroke. Sit-to-stand assessments can be used to detect spinal disorders. However, spinal kinematic measurements require special instrumentation and are expensive. The use of Artificial Intelligence (AI) in pose estimation plays an important role in the assessment or detection of a person's movements. Video-based assessment can be an alternative method that is inexpensive and easy to use. Therefore, this preliminary study proposes a sit-to-stand motion extraction method that uses vision-based pose estimation. Time trends and sit-to-stand trajectories were then calculated for the two videos with different subjects. The results show different trends in both time and trajectory. From this study, it is known that STS time and trajectory are potential features for abnormal detection. This proposed method is expected to be utilized in the medical field to detect movement abnormalities, especially sit-to-stand movements.

Keywords: Sit-to-Stand Analysis, Pose Estimation, Feature Extraction, Human Activity Recognition, Video Processing

Introduction

The Sit-to-Stand (STS) transition is a frequent movement in daily life that requires the coordination of joint movements, including the spine, neck, and hips (trunk). Poor coordination of joint movements during the sit-to-stand transition can be an important indicator of independence and physical health (Melo *et al*., 2022; Roldán Jiménez *et al*., 2019). However, this movement can also be difficult for people with certain health issues such as spinal cord injuries or post-stroke (Waiteman *et al*., 2022; Schwarz *et al*., 2022). Thus, monitoring the kinematic characteristics of the spine during sit-to-stand is important and useful for interventions to improve sit-to-stand movements in spinal disorders.

The main problem with sit-to-stand assessments is the difficulty in measuring spinal kinematics accurately and objectively (Inoue and Matsuo, 2020), which requires specialized instrumentation that is quite expensive (Atrsaei *et al*., 2022). In addition, the measurement of spinal kinematics can also be influenced by factors such as age, sex, and the physical condition of the patient (Nioti *et al*., 2022). Therefore, there is a need for an accurate, objective, and noninvasive method to measure spinal kinematics during sit-to-stand movements using technology that is cheap and easy to use (Erfianto *et al*., 2023).

In a previous study, an RGB-D Camera-based was used as a device for subject video acquisition in sit-to-stand assessment (Acorn *et al*., 2015; Röhling *et al*., 2022; Zhao and Espy, 2019). The drawback of this method is that its use is limited to indoor spaces and is affected by lighting and shadows. Other researchers have used markers for joint marking (Banerjee *et al*., 2014; Tulipani *et al*., 2022; Park *et al*., 2021). The disadvantage of this method is that it requires a procedure for placing the marker on the joint. Other researchers have used Inertial Measurement Units (IMU) (Fudickar *et al*., 2020; Hanawa *et al*., 2019; Buraschi *et al*., 2022; Erfianto and Rizal, 2022) or EMG signals (Wang *et al*., 2022). These devices for data acquisition still need to be more practical for sit-to-stand assessments.

One method that can be used for sit-to-stand assessment is pose estimation. With pose estimation, the joints on the body are estimated using a computer program without requiring an external device placed on the subject's body. Hitherto, pose estimation has been widely used in various applications such as augmented reality, robotics, and human gesture recognition. To develop a system for analyzing trunk movement during sit-to-stand movements, a comparison of several pose estimation methods that have been proven effective, such as OpenPose (Wang *et al*., 2022; Abd Aziz *et al*., 2020; Hsu *et al*., 2019), Alpha Pose (Marusic *et al*., 2023; Li *et al*., 2022) and Media Pipe (Mundt *et al*., 2022), was performed. The use of pose estimation reduces the cost of more complete features.

In this study, a sit-to-stand assessment method that uses pose estimation based on video processing was developed. The main contributions of this study are as follows:

1. To detect landmarks and generate neck, knee, and torso inclination
2. To detect landmarks and generate angular velocity of neck, knee, and torso
3. To provide biomechanical features and signals for sit-to-stand posture

The trunk movement analysis system during sit-to-stand resulting from this proposal will have opportunities to be developed through further research. For example, it can be used to assist sports coaches in analyzing athletes' movements, assist doctors in performing medical rehabilitation and assist product designers in improving the ergonomics of their products. In addition, the system can be used in various other applications that require the analysis of human body movements.

Materials and Methods

Figure (1) shows a diagram of the proposed method. To ensure the reliability of the proposed method, preprocessing techniques were applied to all video data to address potential environmental challenges, such as poor lighting, occlusions, and complex backgrounds. These preprocessing steps included resizing images to a standard resolution to optimize pose estimation and applying background removal to isolate the subject and minimize distractions. These measures reduced noise and variability in the input data, enhancing the accuracy of the pose estimation software and ensuring the consistency of the extracted biomechanical signals. Following this preprocessing, the proposed method was implemented as detailed below.

1. Find points of interest to define sit-to-stand landmarks: We used the right-side sagittal view with the chest cross-hand pose, as displayed in Fig. (2). Two landmarks are used in this STS, namely, joints as landmarks and flexion landmarks. Joint landmarks are the coordinates (x, y) of each joint, as shown in Fig. (2), whereas flexion landmarks include neck flexion, torso flexion, knee flexion, and ankle flexion. These four flexion landmarks were determined from joint landmarks and used to determine the trajectory of the STS movement
2. Find points of interest to define sit-to-stand landmarks: We used the right-side sagittal view with the chest cross-hand pose, as displayed in Fig. (2). Two landmarks are used in this STS, namely, joints as landmarks and flexion landmarks. Joint landmarks are the coordinates (x, y) of each joint, as shown in Fig. (2), whereas flexion landmarks include neck flexion, torso flexion, knee flexion, and ankle flexion. These four flexion landmarks were determined from joint landmarks and used to determine the trajectory of the STS movement
3. Calculate angular values of the neck, torso, and knee The function of this process was to calculate the offset distance. The setup requires the person to be in the proper side view. The main purpose was to determine the offset distance between the two points. It can be the hip point, eyes, or shoulders. These points are always approximately symmetric about the central axis. With this, we will incorporate camera alignment assistance into the script. The distance was calculated using the Euclidean distance formula, as shown in Eq. (1)

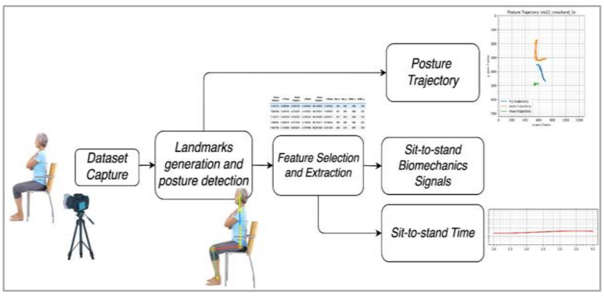


Fig. 1: Diagram block of proposed method

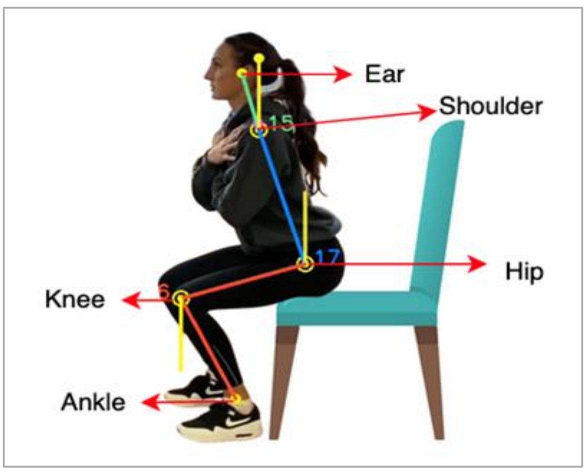


Fig. 2: Joints as a landmark for sit-to-stand assessment

DOI: 10.3844/jcssp.2025.704.712

$$distance = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (1)$$

where:

$$x = position\ in\ the\ x - axis$$

$$y = position\ in\ y\ axis$$

The results of the pose estimation process in the video are shown in Fig. (3). The torso and neck angles, which are used for neck flexion and torso flexion, were estimated for the next analysis.

The next step involves calculating the angular velocity of the neck, torso, and knee. We then calculated the angular velocity of body posture during STS and STS duration. The details of the data collection and feature extraction processes are explained in the following subsections.

Dataset Collection

The Sit-to-Stand (STS) pose starts from the sitting position with the cross-hand on the chest and ends with the sitting position, as displayed in Fig. (4). Practical applications would require a recorded video of a person within five STS activities. To evaluate the proposed methods, we utilized 16 pre-recorded videos collected from YouTube, with metadata listed in Table (1). Additionally, we conducted two rounds of controlled data collection involving eight participants. Each session consisted of 30 seconds of 10 STS transitions recorded before and after the exercise, resulting in 20 unique datasets per participant. This approach ensures the inclusion of varied physical states and enhances the diversity of the dataset, providing a comprehensive basis for analysis. Informed consent was obtained from participants after reading the experimental procedures provided to each participant. By signing the attendance register, participants agree to participate in this research. This primary dataset includes variations in sex, height, weight, and some female subjects wearing the hijab. The video was cut to cover five times the STS, while the frame size did not need to be normalized because the angle between the joints for measuring flexion was not affected by the frame size. In each video, an estimated pose was used to determine the required joint. An example of the initial pose and the results of pose estimation are shown in Fig. (5).

Fig. 3: Original video and its pose estimation process

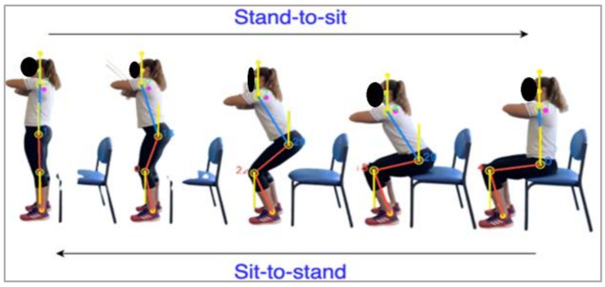


Fig. 4: Sit-to-stand sequences

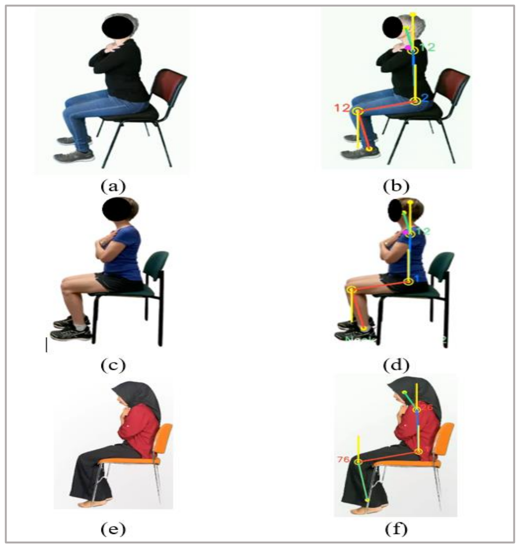


Fig. 5: (a) STS person 1 before pose estimation (b) STS person 1 after pose estimation (c) STS person 5 before pose estimation (d) STS person 5 after pose estimation (e) STS person 15 before pose estimation (f) STS person 15 after pose estimation

Table 1: Metadata of STS video dataset collected from YouTube and primary dataset recording

Video File	File Size (MB)	Frames Size (width, height)	Total Frames
STS_Person_1	3.02	1280x720	649
STS_Person_2	5.01	1280x720	781
STS_Person_3	1.47	1280x720	433
STS_Person_4	3.07	1280x720	271
STS_Person_5	4.45	406x720	891
STS_Person_6	11.88	848x480	1104
STS_Person_7	9.35	800x480	1124
STS_Person_8	7.65	640x368	1076
STS_Person_9	4.29	848x480	995
STS_Person_10	5.31	848x480	1141
STS_Person_11	5.03	848x480	983
STS_Person_12	4.48	848x480	972
STS_Person_13	5.19	848x480	924
STS_Person_14	5.68	848x480	959
STS_Person_15	4.48	848x480	972
STS_Person_16	5.14	848x480	917
STS_Talent_1-40	1.54	1228x720	879

DOI: 10.3844/jcssp.2025.704.712

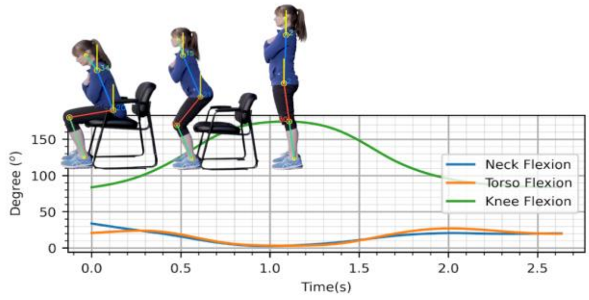


Fig. 6: STS movement and its knee and torso flexion angle for each position

Torso Flexion	v Torso	Neck Flexion	v Neck	Knee Flexion	v Knee	hip_x	hip_y	shldr_x	shldr_y
7.434713	3.890264	9.368702	-4.450290	86.156853	7.223302	493	322	509	200
7.602160	3.462403	9.203022	-4.019332	86.376841	7.049355	491	320	509	200
7.745171	3.025439	9.046302	-3.582426	86.568986	6.889371	491	320	508	200
7.863524	2.582315	8.917525	-3.143023	86.735617	6.748952	490	320	508	200
7.961762	2.134935	8.823931	-2.707098	86.891999	6.631260	490	319	507	200

Fig. 7: Example of feature extracted from flexion and the joint result of pose estimation

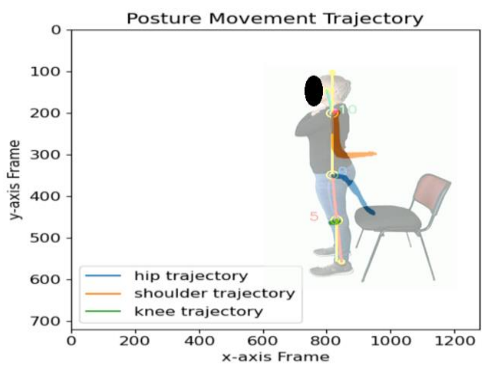


Fig. 8: Hip, shoulder, and knee trajectory

Biomechanical Signals Extracted from Vision-Based Pose Estimation

From the results of the pose estimation, the degree of displacement of each flexion was calculated, as shown in Fig. (6). The values resulting from the movement of each joint are shown in Fig. (7). Later, this STS movement was used to determine the trajectory of the hips, shoulders and knees, as shown in Fig. (8). These results will be used later to determine the trajectory that determines the consistency of STS movement.

Results

Table (2) shows the posture, extracted signal, and trajectory resulting from the sit-to-stand experiments. The resulting biomechanical signals are related to neck, torso, and knee flexion. The details of each signal are shown in Figs. (9-10), respectively. The 2D posture trajectory explains the joint movement during the sit-to-stand activity. This trajectory is projected from the camera frame into the video frame coordinates, that is, in the x- and y-coordinate frames.

Figure (9). shows the angular velocities of the torso, neck, and knee. This graph shows the speed at which the angle of each joint changes in each STS cycle. The sharp peaks indicate relatively fast movement without long transitions and delay during the standing or sitting position, as shown in Figs. (9a-b). Figure (9c) depicts the different biomechanical signals compared to (a and b). Figure (9c) shows the short delay while sitting and standing before the transition. This can be explained by the flat biomechanical signal prior to or after transitions.

The time required to complete the five STS cycles is shown in Fig. (10). The horizontal graph shows the consistency of the time needed to complete the STS, as it happened to person 1. Meanwhile, the graph that shows a rise or fall shows a change in rhythm in STS, which is exemplified in persons 5 and 16. However, Fig. (10c) shows that the time slows after two STS cycles.

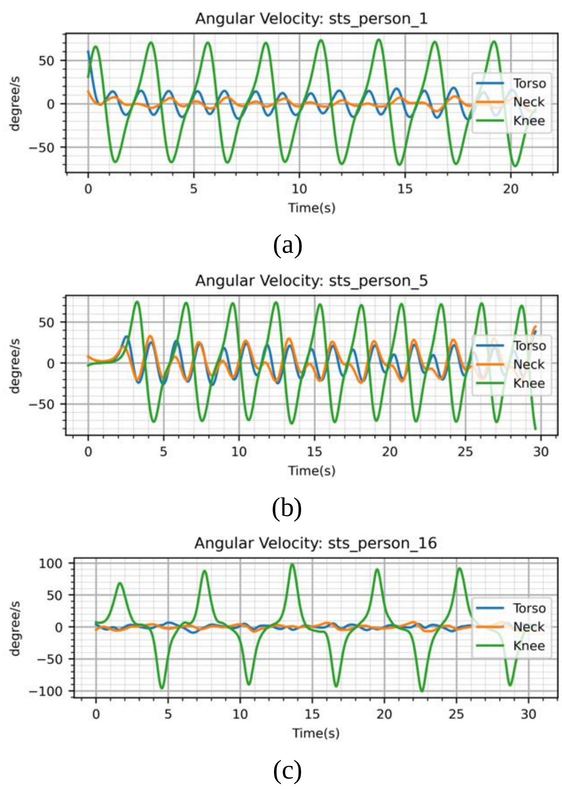
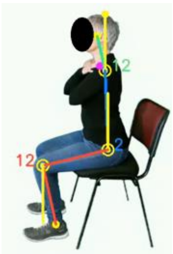
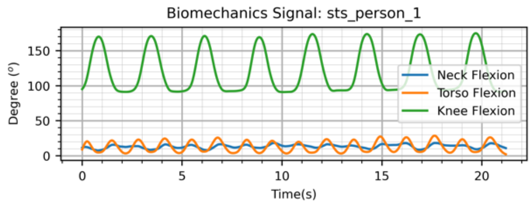
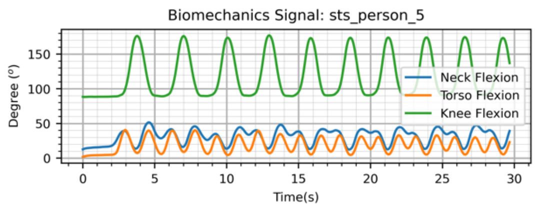
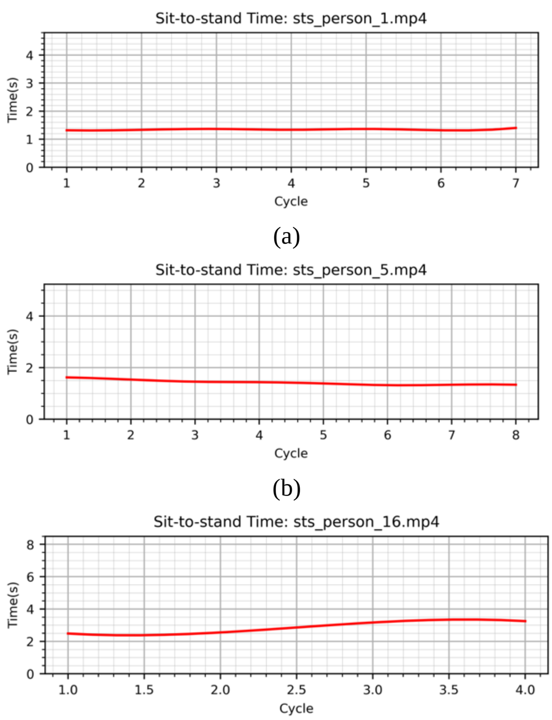


Fig. 9: Angular velocity of neck, torso, and knee (a) Person 1, (b) Person 5, (c) Person 16

DOI: 10.3844/jcssp.2025.704.712

Table 2: From pose video, biomechanics signal and posture trajectory

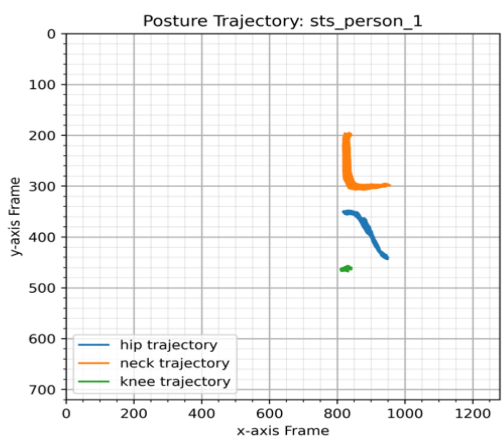
Pose Video	Biomechanics signals	Posture trajectory
 STS_Person_1		
 STS_Person_5		



(a) (b) (c)

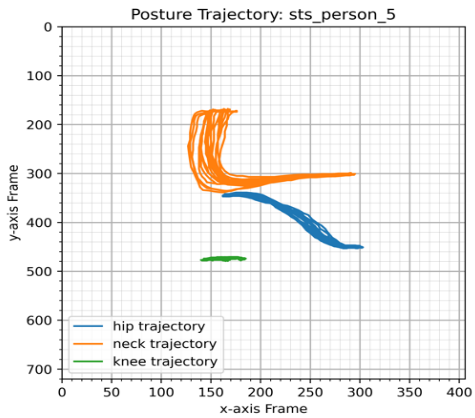
Fig. 10: Trend of sit-to-stand time (a) Person 1 (b) Person 2 (c) Person 16

Figure (11) shows the hip, shoulder, and knee trajectories. A solid image, as in Person 1, visually shows a consistent STS and no significant spread occurs, so that the paths formed almost overlap in one path. Meanwhile, in Persons 5, 16, and 33, the resulting trajectories were spread, depicted by n scattered and inconsistent trajectories. Movement inconsistency may indicate fatigue, abnormalities, or shaking while performing sit-to-stand. The STS time and trajectory results can be potential features for detecting movement abnormalities, especially STS.

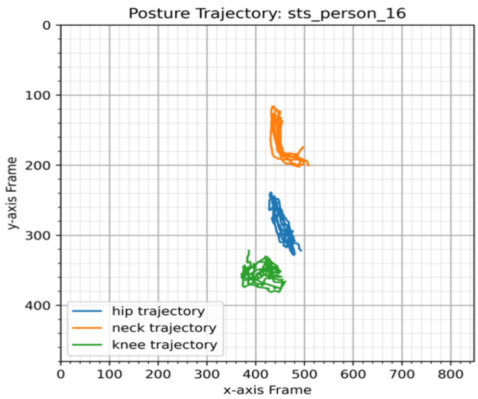


(a)

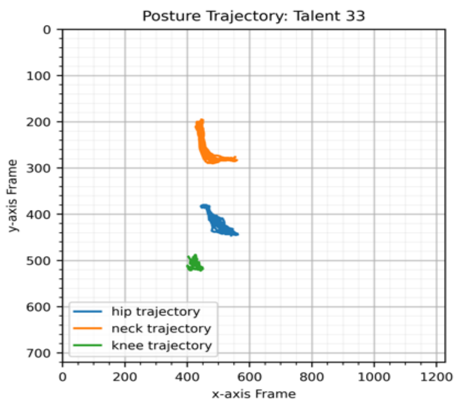
DOI: 10.3844/jcssp.2025.704.712



(b)



(c)



(d)

Fig. 11: Biomechanical trajectory of joint movement

Discussion

In our experiment, significant joints were extracted from the STS analysis. The joint movement in the STS cycle was successfully tracked to depict its trajectory. The angular velocity can be defined and calculated graphically and the trend can be visually distinguished. By examining this trend, it can be determined whether the subject is experiencing fatigue or abnormalities. In this research, automatic condition determination has yet to be carried out because the data are only secondarily recorded. In the next stage, classification is performed using machine learning so that it can be determined when an abnormality occurs in the movement (Zanela *et al*., 2022).

The proposed vision-based pose estimation method offers a non-invasive and cost-effective solution for assessing Sit-to-Stand (STS) transitions compared to Inertial Measurement Units (IMUs), which are widely used for motion analysis. IMUs provide high temporal resolution and precise kinematic data, making them reliable for detecting angular velocity and acceleration during STS tasks; however, they require wearable sensors, which can be uncomfortable and less practical for non-clinical settings. In contrast, vision-based methods eliminate the need for physical attachments, offering greater convenience and accessibility. While IMUs excel in capturing detailed joint movements, vision-based methods can provide a more holistic and scalable approach for real-world applications. A comparative analysis with prior studies, such as Hanawa *et al*. (2019), would be beneficial for research validation, assessing the novelty of the vision-based method, and highlighting its contribution to improving non-invasive motion analysis. This comparison could also validate the effectiveness of the vision-based approach while guiding further enhancements to improve its robustness and usability. In this preliminary study, there are still limitations where the pose estimation algorithm has not been tested at various lighting levels. This is also important because it is to test the reliability of the measurement under various lighting conditions.

Conclusion

This study presents a method for sit-to-stand assessment using pose estimation based on video processing. The proposed method can be used to measure the trajectory and angular velocity of the neck, knee, and torso. Testing with different people shows how quickly each joint's angle changes in each STS cycle and the consistency of the changes in the neck, knees, and torso trajectories. However, in this study, we only show three samples of persons performing sit-to-stand. The preliminary estimates show different time trends and trajectories for the two videos.

Visually, Person 1 exhibited consistent time transitions and trajectories. Meanwhile, persons 5 and 16 generated inconsistent time transitions and dispersed trajectories. A preliminary study showed that biomechanical measurements, including angular velocity and trajectory, could be used as potential features for detecting abnormalities in sit-to-stand movements.

In future work, this research plans to expand the dataset to include a larger and more diverse population, incorporating variations in age, gender, body type, and physical conditions to validate the method's generalizability. Additionally, data will be collected under diverse environmental conditions, such as varying lighting, backgrounds, and occlusions, to further enhance the robustness and applicability of the proposed approach. Incorporating real-time video analysis will be explored to assess STS transitions in more dynamic and varied environments, increasing the method's practicality for real-world applications. Efforts will also be made to refine the pose estimation algorithms to better handle potential disruptions and improve the accuracy of biomechanical measurements. Future studies will focus on integrating machine learning techniques to automate the classification of normal versus abnormal STS movements, providing an automatic and reliable method to assess the performance of the proposed approach in detecting abnormalities. These advancements aim to strengthen the method’s robustness and applicability across diverse scenarios.

Acknowledgment

The authors would like to express their gratitude to the Directorate of Research and Community Service at Telkom University for facilitating this research. This support enabled the project to receive funding from the Directorate of Higher Education, Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia.

Funding Information

The authors received funding from the Directorate of Higher Education, Ministry of Education, Culture, Research and Technology, Republic of Indonesia, under grant 180/E5/PG.02.00. PL/2023 for this research.

Author’s Contributions

Achmad Rizal: Conceptualization and design of the study, evaluation and validation, data collection and video recording, written original draft preparation, writing review and editing the manuscript, supervision, funding acquisition.

Bayu Erfianto: Conceptualization and design of the study, software feature extraction, and methodology, evaluation and validation, formal analysis, data curation, writing original draft preparation, and results visualization.

Sugondo Hadiyoso: Software feature extraction and methodology, formal analysis, written review and editing of the manuscript, research administration.

Istiqomah: Written review and edited the manuscript, research administration.

All authors have read and agreed to the published version of the manuscript.

Ethics

Informed consent was obtained from participants after reading the experimental procedures provided to each participant. By signing the attendance register, participants agree to participate in this research.

References

Abd Aziz, M., Azah Hamzaid, N., Hasnan, N., & Afiq Dzulkifli, M. (2020). MechanomyoGraphy-Based Assessment During Repetitive Sit-to-Stand and Stand-to-Sit in Two Incomplete Spinal Cord-Injured Individuals. *Biomedical Engineering/Biomedizinische Technik*, *65*(2), 175-181. https://doi.org/10.1515/bmt-2018-0200

Acorn, E., Dipsis, N., Pincus, T., & Stathis, K. (2015). Sit-to-Stand Movement Recognition Using Kinect. In A. Gammerman, V. Vovk, & H. Papadopoulos (Eds.), *Statistical Learning and Data Sciences* (Vol. 9047, pp. 179-192). Springer Cham. https://doi.org/10.1007/978-3-319-17091-6_13

Atrsaei, A., Paraschiv-Ionescu, A., Krief, H., Henchoz, Y., Santos-Eggimann, B., Büla, C., & Aminian, K. (2022). Instrumented 5-Time Sit-To-Stand Test: Parameters Predicting Serious Falls Beyond the Duration of the Test. *Gerontology*, *68*(5), 587–600. https://doi.org/10.1159/000518389

Banerjee, T., Skubic, M., Keller, J. M., & Abbott, C. (2014). Sit-to-Stand Measurement for in-Home Monitoring Using Voxel Analysis. *IEEE Journal of Biomedical and Health Informatics*, *18*(4), 1502-1509. https://doi.org/10.1109/jbhi.2013.2284404

Buraschi, R., Pollet, J., Villafañe, J. H., Piovanelli, B., & Negrini, S. (2022). Temporal and Kinematic Analyses of Timed up and go Test in Chronic Low Back Pain Patients. *Gait and Posture*, *96*, 137–142. https://doi.org/10.1016/j.gaitpost.2022.05.027

Erfianto, B., & Rizal, A. (2022). IMU-Based Respiratory Signal Processing Using Cascade Complementary Filter Method. *Journal of Sensors*, *2022*, 1–16. https://doi.org/10.1155/2022/7987159

Erfianto, B., Rizal, A., & Hadiyoso, S. (2023). Empirical Mode Decomposition and Hilbert Spectrum for Abnormality Detection in Normal and Abnormal Walking Transitions. *International Journal of Environmental Research and Public Health*, *20*(5), 3879-4673. https://doi.org/10.3390/ijerph20053879

Fudickar, S., Hellmers, S., Lau, S., Diekmann, R., Bauer, J. M., & Hein, A. (2020). Measurement System for Unsupervised Standardized Assessment of Timed "Up & Go" and Five Times Sit to Stand Test in the Community a Validity Study. *Sensors*, *20*(10), 2824-3007. https://doi.org/10.3390/s20102824

Hsu, Wei-Chun, Chang, Chao-Chin, Lin, Y.-J., Yang, F.-C., Lin, L.-F., & Chou, K.-N. (2019). The Use of Wearable Sensors for the Movement Assessment on Muscle Contraction Sequences in Post-Stroke Patients during Sit-to-Stand. *Sensors*, *19*(3), 657-749. https://doi.org/10.3390/s19030657

Hanawa, H., Hirata, K., Miyazawa, T., Sonoo, M., Kubota, K., Fujino, T., Kokubun, T., & Kanemura, N. (2019). Validity of Inertial Measurement Units in Assessing Segment Angles and Mechanical Energies of Elderly Persons During sit-to-stand motion. *2019 58th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*, 936-940. https://doi.org/10.23919/sice.2019.8859966

Inoue, T., & Matsuo, R. (2020). Prediction of Sit-to-Stand Time Using Trunk Angle and Lower Limb EMG for Assistance System. *2020 IEEE 2nd International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, 1-4. https://doi.org/10.1109/iicaiet49801.2020.9257818

Li, Z., Lu, K., Cai, M., Liu, X., Wang, Y., & Yang, J. (2022). An Automatic Evaluation Method for Parkinson's Dyskinesia Using Finger Tapping Video for Small Samples. *Journal of Medical and Biological Engineering*, *42*(3), 351–363. https://doi.org/10.1007/s40846-022-00701-y

Marusic, A., Nguyen, S. M., & Tapus, A. (2023). Evaluating Kinect, OpenPose and BlazePose for Human Body Movement Analysis on a Low Back Pain Physical Rehabilitation Dataset. *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*, 587-591. https://doi.org/10.1145/3568294.3580153

Melo, L. M., Ansai, J. H., Ferreira, A. C. V. G., Silva, D. C. P., Vale, F. A. C., Takahashi, A. C. M., & Andrade, L. P. (2022). Correlation Between changes in Timed Up and Go performance and Cognition in Older People with Mild Cognitive Impairment: A Longitudinal Study. *Clinical Biomechanics*, *94*, 105620. https://doi.org/10.1016/j.clinbiomech.2022.105620

Mundt, M., Born, Z., Goldacre, M., & Alderson, J. (2022). Estimating Ground Reaction Forces from Two-Dimensional Pose Data: A Biomechanics-Based Comparison of AlphaPose, BlazePose, and OpenPose. *Sensors*, *23*(1), 78-556. https://doi.org/10.3390/s23010078

Nioti, P., Emmanouil, A., & Rousanoglou, E. (2022). Sit-to-Stand and Stand-to-Sit Evaluation in a 62-Year-Old Woman Eleven Years After Her Unilateral Total Hip Arthroplasty. *Journal of Physical Education and Sport*, *22*(5), 1197–1205. https://doi.org/10.7752/jpes.2022.05150

Park, C., Mishra, R., Sharafkhaneh, A., Bryant, M. S., Nguyen, C., Torres, I., Naik, A. D., & Najafi, B. (2021). Digital Biomarker Representing Frailty Phenotypes: The Use of Machine Learning and Sensor-Based Sit-to-Stand Test. *Sensors*, *21*(9), 3258-3304. https://doi.org/10.3390/s21093258

Röhling, H. M., Otte, K., Rekers, S., Finke, C., Rust, R., Dorsch, E.-M., Behnia, B., Paul, F., & Schmitz-Hübsch, T. (2022). RGB-Depth Camera-Based Assessment of Motor Capacity: Normative Data for Six Standardized Motor Tasks. *International Journal of Environmental Research and Public Health*, *19*(24), 16989-17103. https://doi.org/10.3390/ijerph192416989

Roldán Jiménez, C., Bennett, P., Ortiz García, A., & Cuesta Vargas, A. I. (2019). Fatigue Detection During Sit-To-Stand Test Based on Surface Electromyography and Acceleration: A Case Study. *Sensors*, *19*(19), 4202-4352. https://doi.org/10.3390/s19194202

Schwarz, A., Bhagubai, M. M. C., Nies, S. H. G., Held, J. P. O., Veltink, P. H., Buurke, J. H., & Luft, A. R. (2022). Correction to: Characterization of Stroke-Related Upper Limb Motor Impairments Across Various Upper Limb Activities by Use of Kinematic Core set Measures. *Journal of NeuroEngineering and Rehabilitation*, *19*(1). https://doi.org/10.1186/s12984-022-01048-w

Tulipani, L. J., Meyer, B., Fox, S., Solomon, A. J., & Mcginnis, R. S. (2022). The Sit-to-Stand Transition as a Biomarker for Impairment: Comparison of Instrumented 30-Second Chair Stand Test and Daily Life Transitions in Multiple Sclerosis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 1213-1222. https://doi.org/10.1109/tnsre.2022.3169962

Wang, R., An, Q., Yang, N., Kogami, H., Yoshida, K., Yamakawa, H., Hamada, H., Shimoda, S., Yamasaki, H. R., Yokoyama, M., Alnajjar, F., Hattori, N., Takahashi, K., Fujii, T., Otomune, H., Miyai, I., Yamashita, A., & Asama, H. (2022). Clarify Sit-to-Stand Muscle Synergy and Tension Changes in Subacute Stroke Rehabilitation by Musculoskeletal Modeling. *Frontiers in Systems Neuroscience*, *16*, 785143. https://doi.org/10.3389/fnsys.2022.785143

DOI: 10.3844/jcssp.2025.704.712

Waiteman, M. C., Chia, L., Ducatti, M. H. M., Bazett-Jones, D. M., Pappas, E., de Azevedo, F. M., & Briani, R. V. (2022). Trunk Biomechanics in Individuals with Knee Disorders: A Systematic Review with Evidence Gap Map and Meta-analysis. *Sports Medicine - Open*, *8*(1), 145. https://doi.org/10.1186/s40798-022-00536-6

Zhao, W., & Espy, D. D. (2019). Assessment of Sit-to-Stand Movements Using a Single Kinect Sensor. *International Journal of Healthcare Information Systems and Informatics*, *14*(1), 29–43. https://doi.org/10.4018/ijhisi.2019010103

Zanela, A., Schirinzi, T., Mercuri, N. B., Stefani, A., Romagnoli, C., Annino, G., Bonaiuto, V., & Cerroni, R. (2022). Using a Video Device and a Deep Learning-Based Pose Estimator to Assess Gait Impairment in Neurodegenerative Related Disorders: A Pilot Study. *Applied Sciences*, *12*(9), 4642–4799. https://doi.org/10.3390/app12094642