2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Simultaneous Quantification of Personalized Balance, Motion Class and Quality for Whole-body Exercise through Synergy Probe

Felipe M. Ramos[1], Moeko Kojima[1] and Mitsuhiro Hayashibe[1]

***Abstract*— Recently, emerging technologies are being used to solve state of the art problems in rehabilitation and physiotherapy. The increasing power of portable sensors is making a great choice for analysis of movements during daily activities. We previously developed a method to personalize the measure of balance only using kinematic data from Kinect. This paper presents the results of simultaneous quantification for the postural balance, motion classification and its quality with Synergy Probe. Previously, it was not possible to verify what happens when the motion balance is unstable. With motion quality index along with the stability, we can quantitatively evaluate the balance stability considering the motion class and its intensity during whole-body exercise.**

I. INTRODUCTION

In recent years, emerging technologies are being used to solve state of the art problems in rehabilitation and physiotherapy. Serious games and Virtual Reality systems are been used to give motivation and increase participation in the rehabilitation sessions [1]–[3]. The increasing power of wearable and portable sensors is making them a great choice for analysis of movements and daily life activities [4]. In the case of fall risk assessment, research teams are using low-cost devices to measure balance and the risk of fall for the elderly [5], [6].

Our current project focuses on the use of Kinect 2 to calculate a personalized balance measurement for online visualization [6]. The personalized data is more suited, for example, for the elderly, since anthropometric table data are based on the average adult population [7], [8]. Moreover, the use of zero rate of change of angular momentum (ZRAM) [9] allowed the analysis of stability outside the support polygon. The calculation of ZRAM depends only on kinematic data, thereby a force platform is not needed after calibration. This feature gives more freedom of movement, and since the subject does not need to step onto the force platform, there is less risk of falling during rehabilitation sessions for patients.

Although our system gives information about stability, it does not show any information about the movement performance associating to the stability. The operator needs to pay attention to multiple parts of the body and the ZRAM to analyze the part of the movement where the instability occurs. To simplify the observation of the movement and still get useful feedback, we developed the concept of synergy probe to get instant classification and quality of the movement [10] [11]. The algorithm compares the subject's movement with synergies invariant over speed and returns the most similar one and the overall quality. The training phase needs only one recording of each movement to be classified. Also, one set of synergies can be used for different subjects. This paper presents the results of simultaneous quantification both for the personalized balance and motion classification and its quality with synergy probe.

This work was supported by the Japan Society for the Promotion of Science (JSPS) Grant-in-Aid for Scientific Research (B) under Grant 18H01399, and the G-7 Scholarship Foundation.

[1]Felipe M. Ramos, Moeko Kojima and Mitsuhiro Hayashibe are with the Department of Robotics, Graduate School of Engineering, Tohoku University, Sendai, Japan (e-mail: hayashibe@tohoku.ac.jp).

II. METHOD

A. Stability with Zero Rate of change of Angular Momentum

ZRAM is a position on the ground that represents where the reaction force is applied or where it should be applied when the movement is unstable (i.e., the point is outside the support polygon). It can also be interpreted as the position in which a line in the direction of the reaction force passing through the center of mass (CoM) intercepts the ground plane. This position is calculated as [6]

$$p_f = \frac{(p_0 - c) \cdot n}{f \cdot n} f + c, \tag{1}$$

where f is the reaction force, c is the CoM, p_0 is a point defining the ground, n a vector normal to the ground and p_f the ZRAM position. The reaction force f can be estimated as [12]

$$f = M \cdot (\ddot{c} - g), \tag{2}$$

where M is the mass of the subject, g is the gravity, and $\ddot{c}$ the acceleration of CoM.

Since f depends on c and we only need its direction, the only parameter we need to find is c. It can be obtained with the statically equivalent serial chain (SESC) method [13], [14]. The SESC model is a linear system that multiply the orientation of the body segments by a set of parameters specific to the subjects. We used nine segments to represent the body. The specific parameters can be calculated beforehand with a force platform. When the body is not moving, the CoP calculated with the force platform is a good approximation of the ground projection of CoM [13], and if the number of measured postures is large enough, the linear system can be solved without the third dimension of CoM [15].

The stability against the risk of falling is calculated according to the position of p_f in the Minimum Volume Enclosing Ellipsoid (MVEE) [16] of the support polygon. The best stability is achieved when the distance between p_f and the center of the MVEE is 0. The movement is unstable when the distance of p_f to the center is bigger than the distance of the vertices of the support polygon to the center.

These vertices are based on the segments representing the feet that are in contact with the ground. We used one color to visualize the stability of 0 and another color for 1. Any value between is visualized as an interpolation of the two colors.

B. Classification with Synergy Probes

Besides the visualization of stability, we also want to show a simple representation of the movement. We developed in a previous project a system that classifies the full body movements in real-time and also gives a measure to the quality of the movement [10]. The system uses as input the normalized speed of the degrees of freedom (DoFs), thereby it was possible to use the data from Kinect 2 and combine with the stability measurement.

We developed the concept of synergy probes for direct comparison of the synergies with the normalized speed. The classical modular concept of synergies is that the same pattern signal controls different DoFs or muscles, and a movement is a linear combination of synergies [17]. In the case of spatial synergies [18]–[20], the synergies are represented by a matrix W where the rows are the DoFs and the columns are different synergies. The coefficients of the linear combination are represented as a matrix C where the rows are the coefficients of the synergies and the columns are the variation of these coefficients over time. Then, the data V is defined as

$$V = WC. \tag{3}$$

For the synergy probes, the data at a time t is defined as

$$V_n[t] = \frac{V[t]}{n[t]} = WC[t], \tag{4}$$

where $Vn[t]$ is the normalized data and $n[t]$ the normalization factor. The normalization of the data extracts the overall amplitude of the data. Therefore, the steady-state of a movement can be found and stored as a synergy (i.e., a column of W). We used gradient descent with additive rule [21] and a competitive term [10] to iteratively find the synergies that represent the movements in V_n. The equation of the iterative function is

$$W = W + \alpha(V_n C^T\text{-}WCC^T\text{-}\beta), \tag{5}$$

where α is a positive constant and β is a positive constant that decays other synergies so that only one synergy is active at a time. Its values were defined empirically. We update W with Eq. 5 and find C with nonnegative least square [22] until the reconstruction WC converges to V_n.

$V_n[t]$ can be represented as a point moving in the m-dimensional space of the normalized speed of the DoFs. Each position of this space represents a different movement, i.e., a different combination of DoFs. Hence, the synergies are specific points in this space. The classification consist of monitoring how much close $V_n[t]$ is to the synergies. The idea comes from probes monitoring their surroundings. The subject's movement is then classified as the closest synergy probe. Since the synergy probes represent the desired movements, the value of the euclidean distance gives an idea of how good is the subject's movement. Similar to the stability value, we used different colors to represent different synergies. The quality was represented using transparency. A movement is invisible when the distance is more than 0.5 from all synergies, and it is completely opaque when the distance to one synergy is 0.0. The values to control the transparency were decided empirically based on the results of the experiments.

III. Results

We evaluated the ability of the system to show online balance information together with the classification of the movements. The example video can be available at `https://youtu.be/jsgNSSy5gdc`. It can be applicable for multiple users as long as they can be tracked with Kinect. The first half is about stability tracking and the last half is about motion classification while both processes are on-going simultaneously for multiple users.

The classified movements were the lateral raising of both arms, squat, raise right/left leg, and their opposite movements to go back to rest pose. One subject was asked to perform the raise/lower right/left leg movements at a constant speed, and we extracted synergy probes from the data. The other synergies were recycled from previous experiments [10], giving in a total of 8 synergy probes. Since a force platform was not available during the experiments, we calculated ZRAM using parameters from previous experiments [6].

Fig. 1 shows the online visual feedback, classification, quality, and stability when performing squats. The ZRAM arrow turns red when the movement is unstable, and the body segments turn into an opaque color when the subjects perform a movement from the classifier. The segments become transparent when the subject is not doing a movement that is part of the classifier (i.e., all Euclidean distances are below 0.5). We could visualize that most of the instability happened when the segments of the body are more opaque. This change occurs in the middle of the movement, especially when the acceleration of the CoM is high. Another case of instability happens at the beginning of raising one leg, i.e. when the segments change from transparent to opaque during the raising leg movement.

Four subjects were asked to perform the movements twice in the same order and at a comfortable speed. The classifier detects the movements of all subjects. Fig. 2 shows the average quality and stability for each subject and synergy probe when the quality was above 0%. A quality of 0% represents full transparency, and 100% represents full opaque. In general, the cases with lower stability were during squat, and the movement the subjects found more difficult to reproduce was lowering the right leg. Besides that, the results for different subjects demonstrate subject specific patterns. Thus, we can quantify how much each motion class is typical pattern or not as the distance measure obtained by synergy probe. Fig. 2 upper plot demonstrates the motion quality measured by synergy probe.

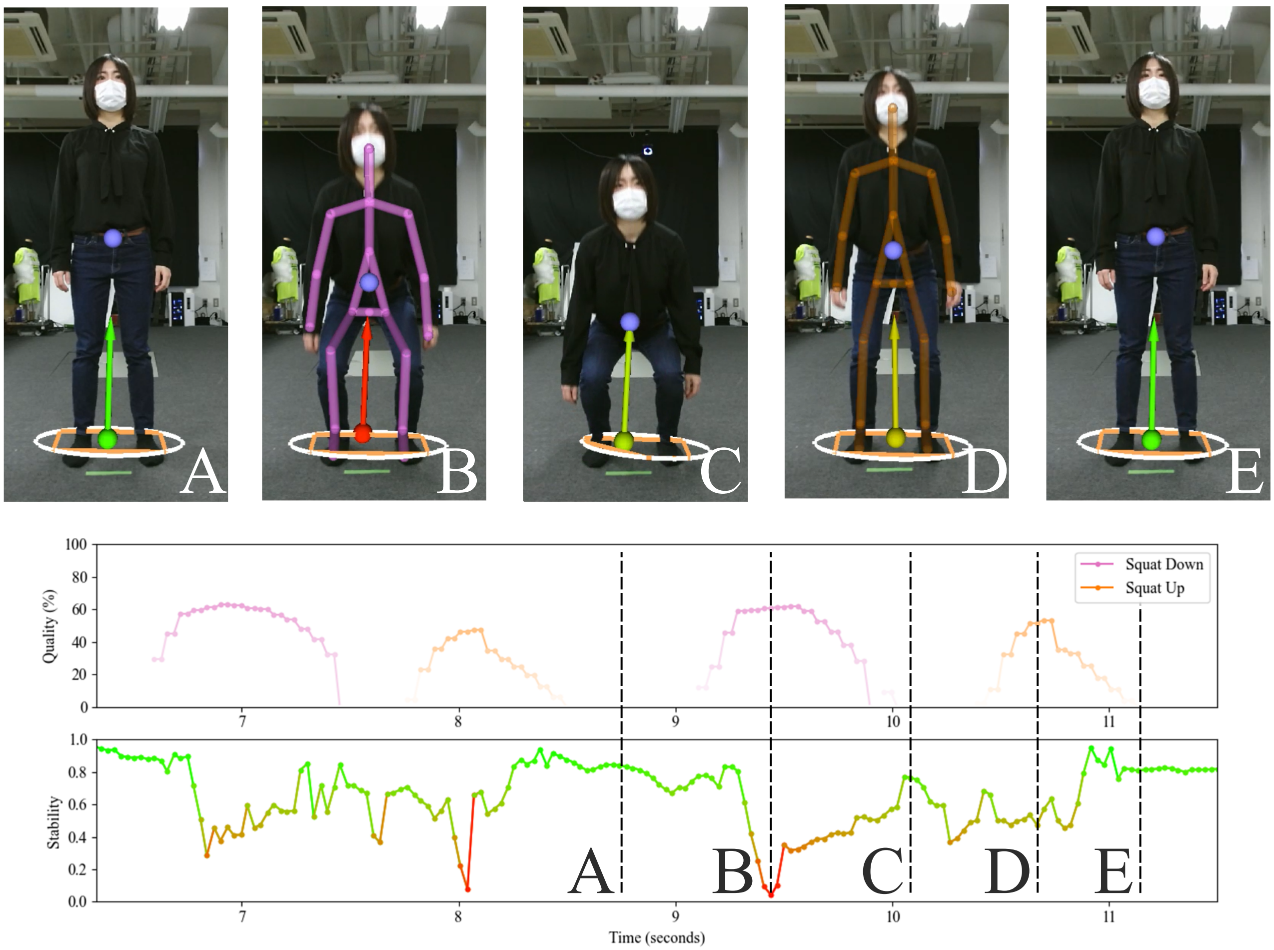

Fig. 1. Personalized balance with classification and quality of movements. (Top) Visual feedback of the subject performing a squat then returning to the rest pose. The arrow represents the position and orientation of ZRAM. The segments appear when the subject goes down (purple) and up (orange). The transparency represents the quality of the movement. The visual feedback also shows the MVEE (white ellipse) and CoM (blue sphere). (Bottom) Quality and stability of the subject while performing two consecutive squats. The colors represent the same information of the (Top) visual feedback. The letters A, B, C, D, E indicate the time of each visual feedback from left to right.

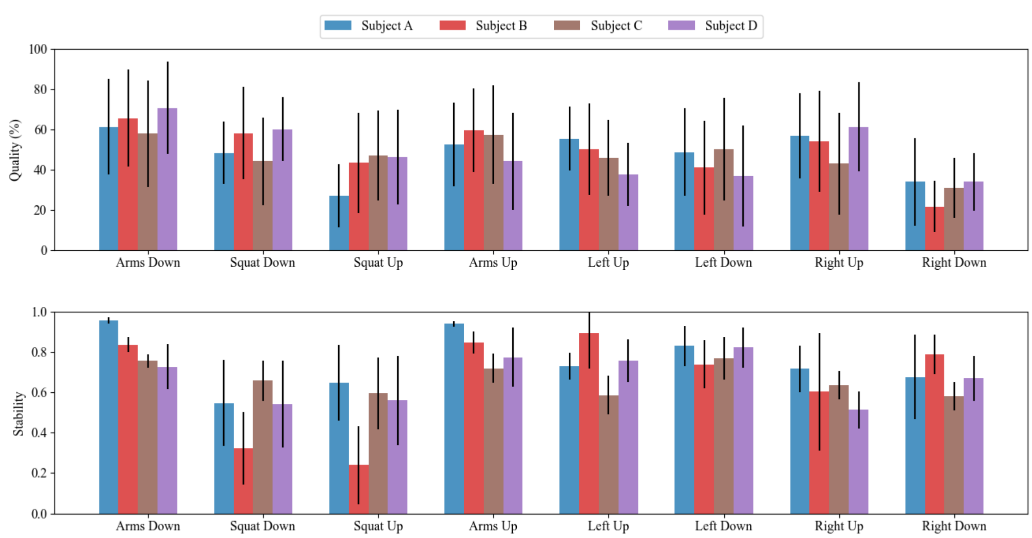

Fig. 2. Average quality (Top) and stability (Bottom) when the quality is above 0%. The black lines are the standard deviation of the data.

It is important to highlight that the contribution of the DoFs during a movement is not steadily constant, and the extracted synergies are an average of that contribution. Therefore, it does not achieve a quality close to 100%. The Euclidean distance in synergy probe is not an absolute motion quality. It is always about relative distance from the template motion pattern in terms of spatiotemporal space. Hence, the quality of the movements is useful especially for comparative evaluation in spatiotemporal space. The detail of synergy probe should be referred to our previous work [10].

IV. Conclusion

The motion classifier through synergy probe associating to the online visualization of personalized balance improved to identify which movement the subject is doing during the balance stability test. In extreme case, the balance score can be good if there is no motion by the subject. Thus, the balance evaluation should be always along with the motion quality evaluation both in a quantitative manner.

The proposed system also enables to identify, for example, if the instability happens at the beginning, in the middle, or at the end of the movement since we can see a change in the transparency or the color of the segments representing the parts of the body for each motion class. The quality of the movements based on the Euclidean distance in Synergy Probe seems to be useful for comparison among subjects and different sessions.

The results indicate that the subjects have their own way to perform the same movement and that is why some can achieve better results in one case but worse results in other cases. However, since all where healthy subjects, they could perform all movements with reasonable quality. Previously, it was not possible to verify what happens when the movement is unstable but it could be potentially different from the desired movements. With motion quality index along with stability, we can now evaluate quantitatively, on whether the subject is properly making the supposed motion to take. Then, while knowing the motion intensity, we can properly evaluate the balance stability with the proposed system.

In the future, we plan to use the system with impaired people and analyze the difference from unimpaired people and their quantitative improvements during rehabilitation.

References

[1] Abel Angel Rendon, Everett B Lohman, Donna Thorpe, Eric G Johnson, Ernie Medina, and Bruce Bradley. The effect of virtual reality gaming on dynamic balance in older adults. Age and Ageing, 41(4):549552, 2012.

[2] Felix Kamieth, Patrick Dähne, Reiner Wichert, Juan Luis Villalar, Viveca Jimenez-Mixco, Antonella Arca, and Maria Teresa Arredondo. Exploring the Potential of Virtual Reality for the Elderly and People with Disabilities. InTech, 2010.

[3] T Saito, N Suzuki, A Hattori, M Hayashibe, S Suzuki, Y Otake, Marker-less whole body skeletal motion analysis based on a body surface model constructed from multi-camera images. Int. Journal of Computer Assisted Radiology and Surgery, vol.1, pages 24-26, 2006.

[4] Shyamal Patel, Hyung Park, Paolo Bonato, Leighton Chan, and Mary Rodgers. A review of wearable sensors and systems with application in rehabilitation. Journal of NeuroEngineering and Rehabilitation, 9:21:1 —-21:17, 2012.

[5] Erik E Stone and Marjorie Skubic. Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. In Proc. of the International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), pages 7177, Dublin, Ireland, 2011.

[6] M Hayashibe, A Gonzlez, and M Tournier. Personalized balance and fall risk visualization with Kinect Two. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020. p. 4863-4866.

[7] David A Winter. Biomechanics and Motor Control of Human Movement. Processing, 2nd(Book, Whole):277, 1990.

[8] Vladimir M Zatsiorsky. Kinetics of Human Motion. Human Kinetics, Champaign, IL, US, 2002.

[9] A Goswami, and V Kallem. Rate of change of angular momentum and balance maintenance of biped robots. In Proc. IEEE International Conference on Robotics and Automation, 2004. ICRA'04. 2004. IEEE, 2004. p. 3785-3790.

[10] Felipe M Ramos, and M Hayashibe. Simultaneous Online Motion Discrimination and Evaluation of Whole-body Exercise by Synergy Probes for Home Rehabilitation. In 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020. p. 10118-10124.

[11] R de Souza Baptista, A.P.L. Bo, and M Hayashibe. Automatic human movement assessment with switching linear dynamic system: motion segmentation and motor performance. IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol.25, no.6, p.628–640, 2016.

[12] S Kajita, H Hirukawa, K Harada, and K Yokoi. Introduction la commande des robots humanoïdes. Paris, France, Springer-Verlag France, 2009.

[13] Sebastien Cotton; Andrew Peter Murray, and Philippe Fraisse. Estimation of the center of mass: from humanoid robots to human beings. IEEE/ASME Transactions on Mechatronics, v. 14, n. 6, p. 707-712, 2009.

[14] A Gonzlez, P Fraisse, and M Hayashibe. An extended statically equivalent serial chain -Identification of whole body center of mass with dynamic motion. Gait and Posture, Vol.84, pp.45-51, 2021.

[15] A Gonzlez, M Hayashibe, V Bonnet, and P Fraisse. Whole body center of mass estimation with portable sensors: Using the statically equivalent serial chain and a kinect. Sensors, v. 14, n. 9, p. 16955-16971, 2014.

[16] Michael J Todd and E Alper Yldrm. On khachiyan ' s algorithm for the computation of minimum-volume enclosing ellipsoids. Discrete Applied Mathematics, 155(13):17311744, 2007.

[17] Andrea D'Avella, and Francesco Lacquaniti. Control of reaching movements by muscle synergy combinations. Frontiers in computational neuroscience, v. 7, p. 42, 2013.

[18] G Rasool, K Iqbal, N Bouaynaya, and G White. Real-time task discrimination for myoelectric control employing task-specific muscle synergies. IEEE transactions on neural systems and rehabilitation engineering, v. 24, n. 1, p. 98-108, 2015.

[19] C W Antuvan, F Bisio, F Marini, S-C Yen, E Cambria, and L. Masia. Role of muscle synergies in real-time classification of upper limb motions using extreme learning machines. Journal of neuroengineering and rehabilitation, v. 13, n. 1, p. 76, 2016.

[20] T Afzal, K Iqbal, G White, and A B Wright. Task discrimination for non-weight-bearing movements using muscle synergies. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015. p. 478-481.

[21] D D Lee, and H S Seung. Algorithms for non-negative matrix factorization. In Advances in neural information processing systems. 2001. p. 556-562.

[22] C L Lawson, and R J Hanson, Solving least squares problems. Siam, 1995, vol. 15.