IMU Sensor Fusion Algorithm for Monitoring Knee Kinematics in ACL Reconstructed Patients

G Bravo-Illanes*[1], RT Halvorson*[2], RP Matthew[1], D Lansdown[2], CB Ma[2], and R Bajcsy[1]

Abstract— **In this paper we propose a sensor embedded knee brace to monitor knee flexion and extension and other lower limb joint kinematics after anterior cruciate ligament (ACL) injury. The system can be easily attached to a standard post-surgical brace and uses a novel sensor fusion algorithm that does not require calibration. The wearable system and the sensor fusion algorithm were validated for various physical therapy exercises against a validated motion capture system. The proposed sensor fusion algorithm demonstrated significantly lower root-mean-square error (RMSE) than the benchmark Kalman filtering algorithm and excellent correlation coefficients (CCC and ICC). The demonstrated error for most exercises was lower than other devices in the literature. The quantitative measures obtained by this system can be used to obtain longitudinal range-of-motion and functional biomarkers. These biomarkers can be used to improve patient outcomes through the early detection of at-risk patients, tracking patient function outside of the clinic, and the identification of relationships between patient presentation, intervention, and outcomes.**

I. INTRODUCTION

Clinical treatment of anterior cruciate ligament (ACL) injuries involves periodic evaluation by a physician while the patient intermittently works with a physical therapist and performs home-based exercises. Whether managed with surgical reconstruction or non-operative modalities, a key component of treatment involves restoring knee kinematics [1]. Continuous monitoring of recovery could improve ACL treatment outcomes by identifying at-risk patients, allowing for earlier treatment, and tracking responses to surgical or rehabilitation programs, especially home-based exercise regimens. The clinical standard for measuring ROM is manual goniometry, a low-cost option that requires a trained operator and may lack accuracy and precision [2]. Alternative approaches to measuring knee kinematics include lab-based systems such as optoelectronics, electromagnetic tracking, and instrumented treadmills which are accurate but more expensive, require trained personnel, and do not allow remote follow-up [3]. An approach using inertial measurement units (IMUs), small electronic components that measure acceleration, angular rate, and magnetic field strength, has the potential to accurately measure knee parameters inexpensively and continuously, without the need for a specialized clinical setting or trained operator. In this paper we propose a knee brace with IMU sensors capable of monitoring lower limb kinematics tailored for ACL recovery.

The use of IMU sensors to compute body joint kinematics has two main challenges: 1) determining the orientation of the sensors and 2) determining the position of the sensors relative to the body. The most basic approach to estimate sensor orientation is to integrate angular velocity over time, but since this approach also integrates error, it produces inaccurate orientation measurements over longer periods of time. This challenge can be tackled using sensor fusion algorithms [4]–[10]. After sensor orientation has been determined, the relative positions of the sensors to the body joint is required to compute joint kinematics. Some authors solve this with manual alignment, which involves the careful placement of sensors over particular body landmarks [4], [11]–[15]. However, this approach is sensitive to sensor placement and requires qualified personnel. As an alternative, other authors propose calibration motions [7], [14] and auto-calibrating systems [5], [10].

In order to have clinical utility, knee kinematic monitoring systems must be easily integrated into the existing orthopedic clinical work flow. None of the aforementioned papers describe hardware that is practical for monitoring patients outside of the clinic, either requiring excessive hardware, specialized clinical settings, or monitoring by trained personnel.

A. Contributions

This paper introduces a knee brace with two IMU sensors, one above and one below the knee, capable of measuring thigh and shank orientation. The main contributions of this work are:

- The proposed system does not require calibration to determine the position of the sensors relative to the patient's body. This makes it easier for patients to use outside of the clinical setting.
- The proposed sensor fusion algorithm integrates the kinematic restrictions of standard post-operative braces with sensor data to accurately monitor leg kinematics with low computational requirements in real-time.
- The sensor fusion algorithm does not rely on magnetometers.
- Since the system is incorporated onto a standard post-operative knee brace already used by ACL patients, the system can be easily integrated into the existing clinical workflow.

The remainder of the paper is organized as follows. Section II presents the mathematical formulation of the

*The first two authors contributed equally to this work.

[1]RP Matthew, R Bajcsy and G Bravo-Illanes are with the Department of Electrical Engineering and Computer Science, University of California at Berkeley, Berkeley, CA 94702 USA

[2]CB Ma, D Lansdown, and RT Halvorson are with the Department of Orthopaedic Surgery, University of California at San Francisco, San Francisco, CA 94143 USA (email: ryan.halvorson@ucsf.edu)

This work was funded by the UCSF Heiman Fellowship

sensor fusion algorithm. Section III presents the experimental validation of the wearable system and the proposed algorithm. Section IV is devoted to the experimental results and discussion which are concluded in Section V.

II. MATHEMATICAL FORMULATION

In this section we propose a sensor fusion algorithm to compute sensor orientation. Sensor fusion algorithms combine data from gyroscopes, accelerometers, and/or magnetometers to estimate orientation. Our proposed filter estimates orientation from accelerometer and gyroscope data while incorporating kinematic restrictions of ACL knee braces.

A. Orientation from angular rate

The change of orientation of a quaternion ${}^S_A\hat{\boldsymbol{q}}$ that represents the orientation of sensor frame A described from a spatial frame S can be expressed in terms of the angular velocity of the sensor ${}^A\omega$ and the quaternion derivative ${}^S_A\dot{\boldsymbol{q}}$ [16] as:

$$ {}^S_A\dot{\boldsymbol{q}} = \frac{1}{2}\,{}^S_A\hat{\boldsymbol{q}} \otimes {}^A\omega \tag{1} $$

The orientation of the frame can be computed numerically by a discretization of (1). Given measurements of the current angular velocity of the sensor (${}^A\omega_{k+1}$), and an estimate of the previous state (${}^S_A\hat{\boldsymbol{q}}_{est,k}$), the new orientation can be estimated using the forward Euler method:

$$ {}^S_A\hat{\boldsymbol{q}}_{\omega,k+1} = {}^S_A\hat{\boldsymbol{q}}_{est,k} +{}^S_A\dot{\boldsymbol{q}}_{\omega,k+1}\Delta t \tag{2} $$

$$ \text{with} \quad {}^S_A\dot{\boldsymbol{q}}_{\omega,k+1} = \frac{1}{2}\,{}^S_A\hat{\boldsymbol{q}}_{est,k} \otimes {}^A\omega_{k+1} \tag{3} $$

where Δt is the sample period.

While the sensor orientation can be estimated from this measurement of angular velocity, gyroscopic drift may lead to inaccuracy. These inaccuracies are corrected through the use of sensor fusion.

B. Proposed sensor fusion algorithm

We propose a sensor fusion algorithm that estimates the orientation of a sensor by combining a quaternion obtained from the integration of the angular velocity over time $\hat{\boldsymbol{q}}_{\omega,k+1}$ (2) and a quaternion obtained from an optimization problem which looks for the optimal orientation aligned with two reference axes $\hat{\boldsymbol{q}}_{\Delta,k+1}$ (6). This idea was inspired by the sensor fusion algorithm proposed by Madgwick in [16].

$$ \hat{\boldsymbol{q}}_{est,k+1} = \gamma_t\hat{\boldsymbol{q}}_{\Delta,k+1} + (1-\gamma)\hat{\boldsymbol{q}}_{\omega,k+1}, \; 0 \le \gamma \le 1 \tag{4} $$

The optimized quaternions (${}^S_A\hat{\boldsymbol{q}}_{\Delta,k+1}$ and ${}^S_B\hat{\boldsymbol{q}}_{\Delta,k+1}$), satisfy the minimization of the the error between the direction of following terms: ${}^A\hat{x}$ axis of sensor A with the ${}^B\hat{x}$ axis of sensor B; acceleration of the sensor A (${}^A\boldsymbol{a}$) with the gravity direction (${}^S\boldsymbol{g}$); and the acceleration of the sensor B (${}^B\boldsymbol{a}$) with the gravity direction (${}^S\boldsymbol{g}$) (5). Both sensors have their $\hat{x}$ axis parallel to patient's knee joint since both sensor are fixed to the knee brace, which restricts movement outside of the flexion and extension axis.

$$ \min_q \frac{1}{2}||\boldsymbol{f}(q)||_2^2 = \min_{{}^S_A\hat{\boldsymbol{q}},{}^S_B\hat{\boldsymbol{q}}} \frac{1}{2}\left|\left|\begin{bmatrix} {}^S_A\hat{\boldsymbol{q}} \otimes {}^A\hat{\boldsymbol{x}} \otimes {}^S_A\hat{\boldsymbol{q}}^* - {}^S_B\hat{\boldsymbol{q}} \otimes {}^B\hat{\boldsymbol{x}} \otimes {}^S_B\hat{\boldsymbol{q}}^* \\ {}^S_A\hat{\boldsymbol{q}}^* \otimes {}^S\boldsymbol{g} \otimes {}^S_A\hat{\boldsymbol{q}} - {}^A\hat{\boldsymbol{a}}_{k+1} \\ {}^S_B\hat{\boldsymbol{q}}^* \otimes {}^S\boldsymbol{g} \otimes {}^S_B\hat{\boldsymbol{q}} - {}^B\hat{\boldsymbol{a}}_{k+1} \end{bmatrix}\right|\right|_2^2 \tag{5} $$

The optimization problem in (5) is solved using a modified gradient descent algorithm with step-size $\mu \in \mathbb{R}_+$. The estimated orientations (${}^A_S\hat{\boldsymbol{q}}_{\Delta,k+1}$ and ${}^B_S\hat{\boldsymbol{q}}_{\Delta,k+1}$) are computed based on previous estimated orientations (${}^S_A\hat{\boldsymbol{q}}_{est,k}$ and ${}^S_B\hat{\boldsymbol{q}}_{est,k}$) and the gradient function (∇F) as:

$$ \hat{\boldsymbol{q}}_{\Delta,k+1} = \hat{\boldsymbol{q}}_{est,k} - \mu\frac{\nabla F(\hat{\boldsymbol{q}}_{est,k})}{||\nabla F(\hat{\boldsymbol{q}}_{est,k})||_2} \tag{6} $$

Where:

$$ \hat{\boldsymbol{q}}_{\Delta,k+1} = \begin{bmatrix} {}^S_A\hat{\boldsymbol{q}}_{\Delta,k+1} \\ {}^S_B\hat{\boldsymbol{q}}_{\Delta,k+1} \end{bmatrix}, \quad \hat{\boldsymbol{q}}_{est,k} = \begin{bmatrix} {}^S_A\hat{\boldsymbol{q}}_{est,k} \\ {}^S_B\hat{\boldsymbol{q}}_{est,k} \end{bmatrix} $$

$$ \nabla F(\hat{\boldsymbol{q}}_{est,k}) = J_f^\top(\hat{\boldsymbol{q}}_{est,k}) \cdot \boldsymbol{f}(\hat{\boldsymbol{q}}_{\boldsymbol{est,k}_k}) $$

Where $J_f(q)$ is the Jacobian of the function $\boldsymbol{f}(q)$.

Since the initial conditions of this algorithm are critical for accurate estimation, we propose an approximation using the alignment of each sensor's acceleration (${}^i\boldsymbol{a},\; i = A, B$) with gravity (${}^S\boldsymbol{g}$). The initial orientation, ${}^S_i\hat{\boldsymbol{q}}_0$, can be obtained as a rotation θ around an axis ${}^S\hat{\boldsymbol{r}}$ [6]:

$$ \theta = \text{acos}\Big({}^i\boldsymbol{a} \cdot {}^S\boldsymbol{g}\Big) \qquad {}^S\hat{\boldsymbol{r}} = \frac{{}^i\boldsymbol{a} \times {}^S\boldsymbol{g}}{||{}^i\boldsymbol{a} \times {}^S\boldsymbol{g}||} $$

$$ {}^S_i\hat{\boldsymbol{q}}_0 = \Big[\cos\Big(\frac{\theta}{2}\Big) \quad \sin\Big(\frac{\theta}{2}\Big) \cdot {}^S\hat{\boldsymbol{r}}\Big] \tag{7} $$

Finally, equations (2), (4) and (6) can be combined since the convergence ratio of $\hat{\boldsymbol{q}}_{\Delta,k+1}$ is equal to or greater than the divergence ratio of $\hat{\boldsymbol{q}}_{\omega,k+1}$, as explained in [16]. In this way, the orientation of each sensor can be obtained as:

$$ \begin{bmatrix} {}^S_A\hat{\boldsymbol{q}}_{est,k+1} \\ {}^S_B\hat{\boldsymbol{q}}_{est,k+1} \end{bmatrix} = \begin{bmatrix} {}^S_A\hat{\boldsymbol{q}}_{est,k} \\ {}^S_B\hat{\boldsymbol{q}}_{est,k} \end{bmatrix} + \left(\begin{bmatrix} {}^S_A\dot{\boldsymbol{q}}_{A_{\omega,k+1}} \\ {}^S_B\dot{\boldsymbol{q}}_{B_{\omega,k+1}} \end{bmatrix} - \beta\dot{\hat{\boldsymbol{q}}}_{\epsilon,k+1}\right)\Delta t \tag{8} $$

$$ \text{with} \quad \dot{\hat{\boldsymbol{q}}}_{\epsilon,k+1} = \frac{\nabla F(\hat{\boldsymbol{q}}_{est,k})}{||\nabla F(\hat{\boldsymbol{q}}_{est,k})||_2} \tag{9} $$

Fig. 1 depicts a block diagram for our proposed filter used to obtain the orientation of the system.

C. Joint Angles

The hardware design includes two IMU sensors, one above the knee and the other below, placed as shown in Fig. 2. The sensor fusion algorithm proposed allows computation of orientation of the thigh and the shank. Comparison of these orientations allows computation of lower limb angles.

The orientation of sensor B described from sensor A (${}^A_B\hat{\boldsymbol{q}}$) gives the relative rotation between the shank and the thigh, allowing for computation of the knee flexion angle.

Knee abduction and adduction, valgus and varus, and internal and external rotation are restricted by the knee brace since these types of movements can negatively affect post-ACL injury or post-surgical recovery.

For this paper, the steps for the computation of the flexion angle between the sensors are:

1) Compute quaternions for sensors A and B.

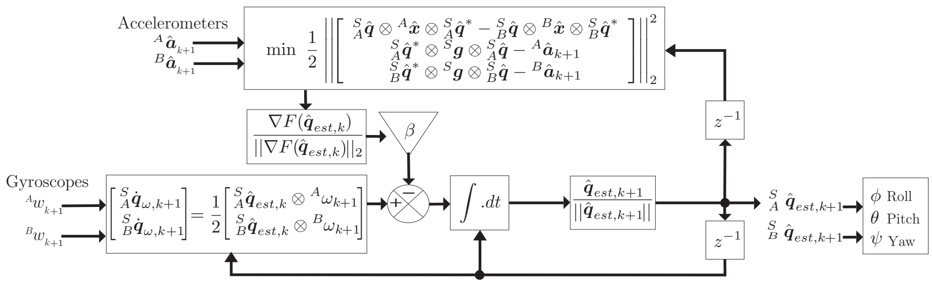

Fig. 1. Block diagram representation of the proposed filter to compute the angle between 2 IMU sensors with a parallel axis.

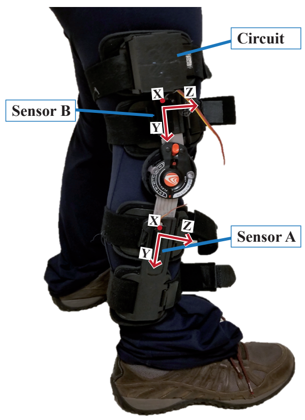

Fig. 2. Sensor placement along a standard ACL knee brace. Sensors and circuitry are held inside 3D printed boxes which are adhered the side of the brace (Breg T-Scope). Sensor orientation is depicted for each sensor.

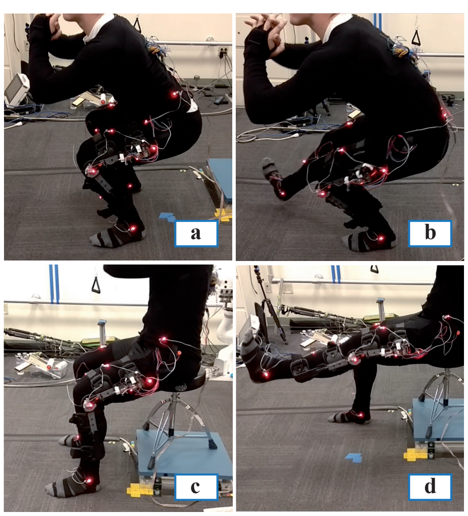

Fig. 3. Physical therapy exercises validated with optical motion capture. The subject was fitted with a prototype brace and LED markers on his left leg. The exercises depicted in the figure: a) Double leg squats (DLS), b) Single leg squats (SLS), c) Sit stand movements (STS), d) Seated leg extensions (SLE)

2) Compute the quaternion corresponding to the rotation from sensor A to sensor B, ${}^{A}_{B}\hat{\boldsymbol{q}}$

$$ {}^{A}_{B}\hat{\boldsymbol{q}} = {}^{A}_{S}\hat{\boldsymbol{q}} \otimes {}^{S}_{B}\hat{\boldsymbol{q}} = {}^{S}_{A}\hat{\boldsymbol{q}}^{*} \otimes {}^{S}_{B}\hat{\boldsymbol{q}} \tag{10} $$

3) Computation of the roll angle (ϕ) of an Euler $\mathtt{ZYX}$ rotation that is equivalent to the rotation represented by the quaternion ${}^{A}_{B}\hat{\boldsymbol{q}} = [q_1\ q_2\ q_3\ q_4]$.

$$ \phi = \operatorname{atan2}\big(2q_3q_4 + 2q_1q_2,\ 2q_1^2 + 2q_4^2 - 1\big) \tag{11} $$

III. Experimental Validation

In order to evaluate the feasibility of the proposed wearable system and its sensor fusion algorithm, a prototype (Fig. 2) was validated against a gold standard optical motion capture system (MOCAP) on a non-clinical subject.

Code for data acquisition, sensor fusion algorithms and other analyses can be found in *https://doi.org/10.24433/CO.0241839.v2*

A. Experimental Protocol

All experimental protocols were approved by University of California, San Francisco IRB 18-25201. A subject (Male, age: 23) was recruited under informed consent and was fitted with a prototype on his left leg. Fourteen LED markers were attached to the subject's legs and hips using Velcro.

The subject was asked to perform double leg squats (DLS), single leg squats (SLS), sit stand movements (STS) and seated leg extensions (SLE) (Fig. 3). Three trials of five repetitions per exercise were recorded.

An 8-camera active MOCAP system was used in this study to provide a ground-truth estimate of position and orientation of each body segment. Motion data was simultaneously recorded from the prototype and the motion capture system. Motion capture data was recorded at 480 Hz and the IMU sensors raw data at 49 Hz. Both data were manually synchronized.

B. Data Analysis

All signals captured in the experiment were processed offline using *MATLAB*™. The performance of the sensor fusion algorithms were compared against the MOCAP data using three statistical measures:

1) Root-mean-square error (RMSE): identifies difference (error) between the predicted and reference value in degrees.

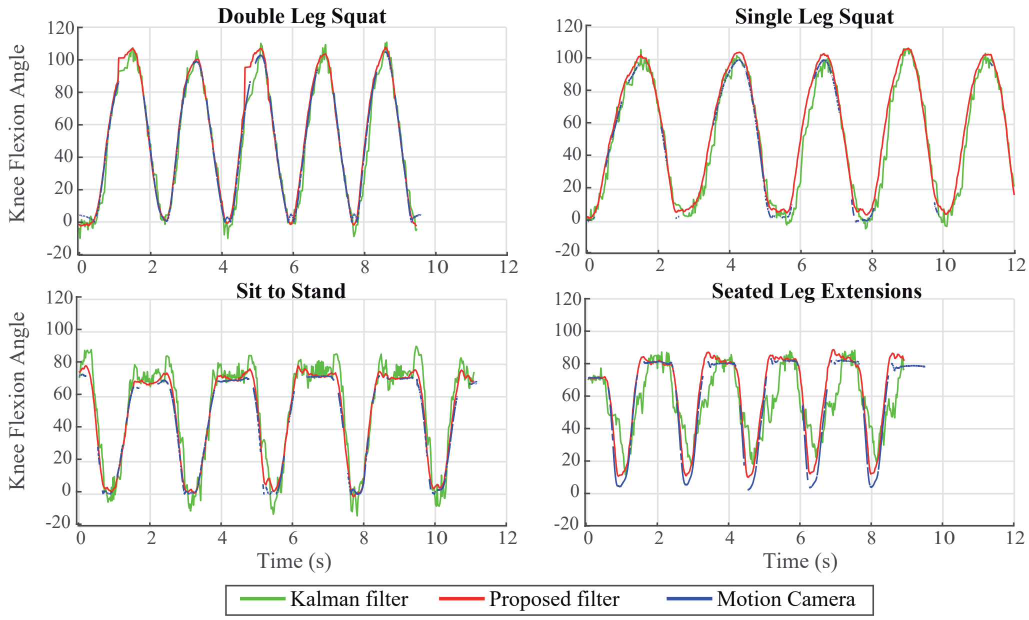

Fig. 4. Knee flexion angle vs time for four physical therapy exercises. Optical motion capture (blue), Kalman filter (green), and our proposed filter (red). 0 degrees implies a fully extended leg.

2) Lin's Concordance Correlation Coefficient (CCC): identifies the correlation between the predicted and reference values.
3) Inter-class Correlations Coefficients (ICC): identifies the absolute agreement (ICC(2,1)) and relative consistency (ICC(3,1)) between the predicted and reference values. ICC values were interpreted as poor (< 0.5), moderate ($0.5-0.75$), good ($0.75-0.9$), and excellent (> 0.9).

IV. Results and Discussion

Knee flexion angles computed by the Kalman-filter algorithm adapted from Wang *et al.* [17] and our proposed algorithm are compared with the MOCAP angles in Fig. 4. RMSE, CCC, and ICC statistics are shown in Table I.

Reliability (CCC), relative consistency (ICC(3,1)), and absolute agreement (ICC(2,1)) were excellent for both algorithms in most exercises (DLS, SLS, STS), with the proposed algorithm slightly outperforming the Kalman-filter algorithm.

Our proposed hardware and sensor fusion algorithm performance is compared with knee extension tracking systems in Table II. The proposed system offers more accurate estimation than those proposed by McGrath *et al.* and Takeda *et al.*, but slightly less accurate than Dejnabadi *et al.* and Favre *et al.* It should be noted that Favre's algorithm requires specific calibration motions and Dejnabadi's algorithm depends on measurements of sensor position relative to body segments. Our hardware and proposed algorithm require neither calibration motions nor measurements. Additionally, our sensor fusion algorithm exhibited similar or better performance to auto-calibrating systems (Seel and McGrath).

Both sensor fusion algorithms performed worse in seated leg extensions (SLE) than the other exercises. In both cases, this error increase may be attributed to fast movements with large centripetal accelerations [13]. Our proposed algorithm still presents excellent correlation coefficients, and is more reliable, consistent, and agreeable than the Kalman-filter algorithm. This difference is likely observed because the Kalman-filter algorithm relies only on the direction of gravity to improve the estimated sensor orientation, while our proposed filter also uses the range of motion restriction of the knee brace.

TABLE I

Performance of sensor fusion algorithms against optical motion capture in the estimation of knee flexion angle

Exercise	Measure	Proposed	Kalman-filter
DLS	RMSE (deg)	2.8 ± 0.9	7.8 ± 2.0
	CCC	0.997	0.976
	ICC(2,1)	0.997	0.946
	ICC(3,1)	0.997	0.979
SLS	RMSE (deg)	4.8 ± 1.0	8.5 ± 3.3
	CCC	0.998	0.929
	ICC(2,1)	0.986	0.959
	ICC(3,1)	0.987	0.970
STS	RMSE (deg)	2.3 ± 0.2	9.8 ± 3.1
	CCC	0.996	0.944
	ICC(2,1)	0.996	0.944
	ICC(3,1)	0.997	0.955
SLE	RMSE (deg)	6.5 ± 1.6	18.9 ± 4.8
	CCC	0.974	0.718
	ICC(2,1)	0.970	0.719
	ICC(3,1)	0.988	0.735

DLS: Double leg squats, SLS: single leg squats, STS: sit stand movements, SLE: seated leg extensions

V. Conclusion

In this work a knee brace with IMU sensors and a sensor fusion algorithm is proposed to compute knee flexion

TABLE II

COMPARISON OF THE PROPOSED HARDWARE AND SENSOR FUSION ALGORITHM AGAINST OTHER KNEE EXTENSION TRACKING SYSTEMS

Source	**RMSE** (deg)	**CCC**
Proposed Filter	**2.8-6.5**	**0.974-0.998**
Favre *et al.*[7].	1.5	1.000
Dejnabadi *et al.* [12]	1.3	0.997
Kawano *et al.* [11]	—	0.984
Cooper *et al.* [4]	0.7-3.4	—
Schepers *et al.* [9]	3.6	—
Seel *et al* [10]	4.0	—
Liu *et al.* [14]	4.4	0.912
Takeda *et al.* [15]	6.8	0.920
McGrath *et al.* [5]	9.2	—

Values with — were not reported by the author

angle. The combination of the proposed knee brace and sensor fusion algorithm provides multiple benefits that make this wearable system a robust solution for monitoring ACL patients within the existing clinical work flow. The knee brace is easy for patients to use and does not require calibration to determine the relative position of sensors to the body. Moreover, the sensor fusion algorithm does not rely on magnetometers and can compute flexion angles in real-time due to low computational requirements. These characteristics make the proposed wearable system a good option to track joint kinematics because it does not require a trained technician, can be worn outside the clinic, and can provide a continuous stream of data for both the patient and provider. The device could also be used by patients in home-based rehabilitation to track progress, assist in successful completion of exercises, and reduce non-adherence.

The performance of the proposed wearable system and sensor fusion algorithm during knee flexion and extension was evaluated in this paper. The proposed algorithm demonstrated better performance that a benchmark Kalman filter algorithm, providing an accurate and reliable estimation (CCC and ICC > 0.97), with a RMSE less than 6.5 deg. in the validation experiments.

In future work, the proposed system and fusion algorithm will be validated in other lower limb angles such as hip abduction/adduction and hip internal/external rotation. Future prototypes could include other data, such as surface electromyography to further track patient rehabilitation as in [18].

ACKNOWLEDGEMENT

The authors are grateful to the Heiman Family and the Heiman Fellowship for funding, and to Rodrigo Henriquez-Auba for his insightful discussions.

REFERENCES

[1] S. Brandsson, J. Karlsson, L. Swärd, J. Kartus, B. I. Eriksson, and J. Kärrholm, "Kinematics and laxity of the knee joint after anterior cruciate ligament reconstruction: pre-and postoperative radiostereometric studies," *The American journal of sports medicine*, vol. 30, no. 3, pp. 361–367, 2002.

[2] R. M. F. d. Carvalho, N. Mazzer, and C. H. Barbieri, "Analysis of the reliability and reproducibility goniometry photogrammetry regarding the hand," *Acta ortopedica brasileira*, vol. 20, no. 3, pp. 139–149, 2012.

[3] S. Bottone, D. Demarchi, and S. Tedesco, "Acl rehabilitation: An inertial sensors-based approach for functional assessment and progress monitoring," Ph.D. dissertation, Politecnico di Torino, 2018.

[4] G. Cooper, I. Sheret, L. McMillian, K. Siliverdis, N. Sha, D. Hodgins, L. Kenney, and D. Howard, "Inertial sensor-based knee flexion/extension angle estimation," *Journal of biomechanics*, vol. 42, no. 16, pp. 2678–2685, 2009.

[5] T. McGrath, R. Fineman, and L. Stirling, "An auto-calibrating knee flexion-extension axis estimator using principal component analysis with inertial sensors," *Sensors (Basel, Switzerland)*, vol. 18, no. 6, 2018.

[6] J. Favre, B. Jolles, O. Siegrist, and K. Aminian, "Quaternion-based fusion of gyroscopes and accelerometers to improve 3d angle measurement," *Electronics Letters*, vol. 42, no. 11, pp. 612–614, 2006.

[7] J. Favre, B. Jolles, R. Aissaoui, and K. Aminian, "Ambulatory measurement of 3d knee joint angle," *Journal of biomechanics*, vol. 41, no. 5, pp. 1029–1035, 2008.

[8] R. Zhu and Z. Zhou, "A real-time articulated human motion tracking using tri-axis inertial/magnetic sensors package," *IEEE Transactions on Neural systems and rehabilitation engineering*, vol. 12, no. 2, pp. 295–302, 2004.

[9] H. M. Schepers, D. Roetenberg, and P. H. Veltink, "Ambulatory human motion tracking by fusion of inertial and magnetic sensing with adaptive actuation," *Medical & biological engineering & computing*, vol. 48, no. 1, p. 27, 2010.

[10] T. Seel, J. Raisch, and T. Schauer, "Imu-based joint angle measurement for gait analysis," *Sensors*, vol. 14, no. 4, pp. 6891–6909, 2014.

[11] K. Kawano, S. Kobashi, M. Yagi, K. Kondo, S. Yoshiya, and Y. Hata, "Analyzing 3d knee kinematics using accelerometers, gyroscopes and magnetometers," in *System of Systems Engineering, 2007. SoSE'07. IEEE International Conference on*. IEEE, 2007, pp. 1–6.

[12] H. Dejnabadi, B. M. Jolles, and K. Aminian, "A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 8, pp. 1478–1484, 2005.

[13] H. Dejnabadi, B. M. Jolles, E. Casanova, P. Fua, and K. Aminian, "Estimation and visualization of sagittal kinematics of lower limbs orientation using body-fixed sensors," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. LMAM-ARTICLE-2006-003, pp. 1385–1393, 2006.

[14] K. Liu, T. Liu, K. Shibata, and Y. Inoue, "Ambulatory measurement and analysis of the lower limb 3d posture using wearable sensor system," in *Mechatronics and Automation, 2009. ICMA 2009. International Conference on*. IEEE, 2009, pp. 3065–3069.

[15] R. Takeda, S. Tadano, A. Natorigawa, M. Todoh, and S. Yoshinari, "Gait posture estimation using wearable acceleration and gyro sensors," *Journal of biomechanics*, vol. 42, no. 15, pp. 2486–2494, 2009.

[16] S. Madgwick, "An efficient orientation filter for inertial and inertial/magnetic sensor arrays," *Report x-io and University of Bristol (UK)*, vol. 25, 2010.

[17] L. Wang, Z. Zhang, and P. Sun, "Quaternion-based kalman filter for ahrs using an adaptive-step gradient descent algorithm," *International Journal of Advanced Robotic Systems*, vol. 12, no. 9, p. 131, 2015.

[18] O. A. Malik, S. A. Senanayake, and D. Zaheer, "An intelligent recovery progress evaluation system for acl reconstructed subjects using integrated 3-d kinematics and emg features." *IEEE J. Biomedical and Health Informatics*, vol. 19, no. 2, pp. 453–463, 2015.