UNIVERSITY OF LEEDS

This is a repository copy of *Hybrid Position and Orientation Tracking for a Passive Rehabilitation Table-Top Robot*.

White Rose Research Online URL for this paper:
http://eprints.whiterose.ac.uk/117269/

Version: Accepted Version

Proceedings Paper:
Wojewoda, KK, Culmer, PR, Gallagher, JF et al. (2 more authors) (2017) Hybrid Position and Orientation Tracking for a Passive Rehabilitation Table-Top Robot. In: Proceedings of the 2017 International Conference on on Rehabilitation Robotics (ICORR). IEEE-RAS-EMBS International Conference on Rehabilitation Robotics (ICORR 2017), 17-20 Jul 2017, London, UK. IEEE , pp. 702-707. ISBN 978-1-5386-2296-4

https://doi.org/10.1109/ICORR.2017.8009330

© 2017 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other users, including reprinting/ republishing this material for advertising or promotional purposes, creating new collective works for resale or redistribution to servers or lists, or reuse of any copyrighted components of this work in other works. Uploaded in accordance with the publisher's self-archiving policy.

Reuse
Unless indicated otherwise, fulltext items are protected by copyright with all rights reserved. The copyright exception in section 29 of the Copyright, Designs and Patents Act 1988 allows the making of a single copy solely for the purpose of non-commercial research or private study within the limits of fair dealing. The publisher or other rights-holder may allow further reproduction and re-use of this version - refer to the White Rose Research Online record for this item. Where records identify the publisher as the copyright holder, users can verify any specific terms of use on the publisher's website.

Takedown
If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

White Rose
university consortium
Universities of Leeds, Sheffield & York

eprints@whiterose.ac.uk
https://eprints.whiterose.ac.uk/

Hybrid Position and Orientation Tracking for a Passive Rehabilitation Table-Top Robot

K. K. Wojewoda, P. R. Culmer, J. F. Gallagher, A. E. Jackson and M. C. Levesley

Abstract— This paper presents a real time hybrid 2D position and orientation tracking system developed for an upper limb rehabilitation robot. Designed to work on a table-top, the robot is to enable home-based upper-limb rehabilitative exercise for stroke patients. Estimates of the robot's position are computed by fusing data from two tracking systems, each utilizing a different sensor type: laser optical sensors and a webcam. Two laser optical sensors are mounted on the underside of the robot and track the relative motion of the robot with respect to the surface on which it is placed. The webcam is positioned directly above the workspace, mounted on a fixed stand, and tracks the robot's position with respect to a fixed coordinate system. The optical sensors sample the position data at a higher frequency than the webcam, and a position and orientation fusion scheme is proposed to fuse the data from the two tracking systems. The proposed fusion scheme is validated through an experimental set-up whereby the rehabilitation robot is moved by a humanoid robotic arm replicating previously recorded movements of a stroke patient. The results prove that the presented hybrid position tracking system can track the position and orientation with greater accuracy than the webcam or optical sensors alone. The results also confirm that the developed system is capable of tracking recovery trends during rehabilitation therapy.

I. INTRODUCTION

In England, 110,000 cases of stroke are reported each year and 300,000 people are suffering post-stroke disabilities. These numbers are projected to rise due to the ageing of the English population [1, 2]. Although, initial hospital post-stroke rehabilitation is comprehensive, patients frequently do not completely achieve long-term recovery goals. This is exacerbated by a lack of adequate therapeutic intervention after discharge from hospital, primarily caused by limited economic resources and a lack of qualified physiotherapists [3]. An emerging approach to promote upper limb rehabilitation beyond hospital stay is the use of table-top passive rehabilitation robots which do not require professional supervision, such as the Arm Skate [4], ARMassist [5] and Reha-Maus [6]. These devices are designed to monitor arm movements, hence provide recovery feedback, and support rehabilitation protocols embedded in video games, which have been confirmed to boost patient attention and rehabilitation results [7]. To record the patient's efforts while performing a rehabilitation exercise (game), each of the three mentioned passive rehabilitation robots incorporates a positioning system tracking their 2D position and for the ARMassist and Reha-Maus also their orientation. The Arm Skate utilizes a webcam to estimate the absolute position of the robot. The ARMassist uses three mouse optical sensors, one tracks the absolute position relative to a coded mat, and two optical sensors track relative position changes relative to the mat, and absolute and relative position data is fused to provide more accurate position and orientation estimates. Likewise, the Reha-Maus utilizes two subsystems: relative based on wheels odometry, and absolute, based on an infrared camera mounted above it.

The accuracy of the developed position tracking systems for these table-top rehabilitation robots has not, for the most part, been comprehensively evaluated for the use in rehabilitation and tracking recovery changes in patients. To address this problem, an innovative 2D hybrid position and orientation tracking system is presented and experimentally evaluated in this work. It is validated through an experimental set-up whereby the rehabilitation robot is moved by a humanoid robotic arm replicating previously recorded movements of a stroke patient. The system is designed to monitor movements of a passive rehabilitation robot, which is presented in Figure 1 (a and c). The system fuses position data from a webcam and two optical mouse sensors. The webcam is positioned directly above the workspace, mounted on a fixed stand, and tracks the robot's absolute position by detecting two markers fixed on top of the robot (Figure 1b). Two laser optical sensors are mounted on the underside of the robot (Figure 1d) and track the relative motion of the robot with respect to the surface on which it is placed. Utilizing the webcam enables the tracking system to record videos of rehabilitation exercises performed by a patient' which can be beneficial for medical evaluation, especially during home based rehabilitation therapy.

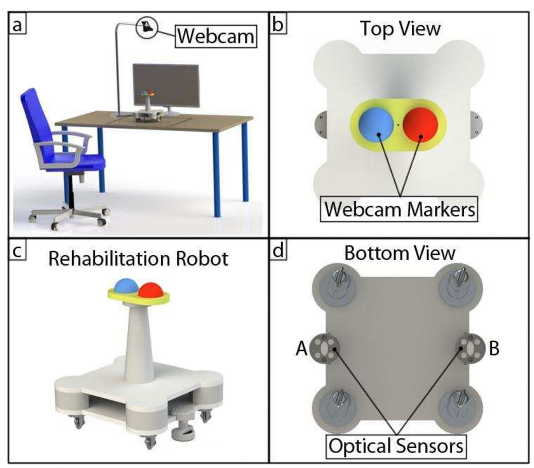

Figure 1. a) Conceptual setup of a passive table-top rehabilitation system, b) Top view of the robot presenting blue and red webcam markers, c) The rehabilitation robot, d) Bottom view of the robot presenting A and B mouse optical sensors. The actuated module of the robot is not presented here.

*Research supported by EPSRC.

All authors are with the School of Mechanical Engineering, University of Leeds, Leeds, UK (e-mail: mnkkw@ leeds.ac.uk).

The presented work is a continuation of the work previously shown in [8], which proved that the 2D position tracking system fusing position estimates from two sensors, an optical mouse sensor and a webcam, can estimate the position with greater accuracy than would be possible using each sensor alone. In this paper, the functionality of the hybrid tracking system [8] is extended by including orientation tracking. The tracking system introduced in [8] could not track rotation and could not function properly if rotation of the tracked object occurred.

Sensor fusion models greatly depend on the application, thus there is no general solution of sensor fusion [9]. A sensor fusion can by performed at multiple levels of fusion, depending on the number and types of sensors [10]. In this work, the fusion algorithm performs a two-level fusion. First, data from two optical sensors is integrated together and secondly the data from the optical sensors and the webcam is fused.

The main requirements of the developed 2D position and orientation tracking system are supporting rehabilitation games and tracking recovery trends during rehabilitation therapy while using the rehabilitation robot (Figure 1c). These are discussed in this paper.

II. Hybrid Position and Orientation Tracking System

The developed hybrid tracking system fuses position and orientation measurements from two subsystems: absolute and relative position and orientation tracking systems.

A. Webcam-based absolute position and orientation tracking

The absolute position tracking subsystem is based on a Logitech Pro 9000 webcam. The webcam is attached to a fixed stand (Figure 1a) and detects the motion of the robot (Figure 1c) by detecting two markers, blue and red (Figure 1b), which are 40 mm in diameter. The webcam absolute tracking algorithm works in 5 main steps:

1. Acquire a frame.
2. Apply a calibration filter.
3. Detect the blue marker centre coordinates.
4. Detect the red marker centre coordinates.
5. Calculate the robot's position and orientation.

The robot's 2D position and orientation are calculated based on the centre coordinates of the blue and red markers.

B. Optical sensors-based relative position and orientation tracking

The relative position tracking is based on two ADNS-9800 laser optical mouse sensors. The optical sensors, labelled A and B, are mounted on the underside of the robot, as shown in Figure 1d. The optical sensors hover around 2.4 mm above the surface and track the position changes relative to the starting position. The operation of the relative tracking system can be summarised in 3 steps:

1. Read A sensor coordinates increments.
2. Read B sensor coordinates increments.
3. Calculate robot's position and orientation increments.

C. Fusion scheme

The data sample rate is different for both the webcam and the optical sensors. The webcam sampling frequency is assumed to always be slower than the sampling frequency of the optical sensors. The fused trajectory is based on optical sensors measurements with the webcam measurements being used to correct the accumulative error (drift) inherent in the optical sensor.

When the fusion algorithm is running, two different cases are utilized based on the availability of the webcam data, a case when webcam data is available and a case when it is not. This approach is related to the fusion strategy presented in [6], but in the presented fusion scheme a Kalman filter is not implemented to fuse data and correct accumulative odometry errors.

The operation of the proposed tracking system can be described in 3 steps:

1. Reading measurements from the sensors.

The generalized position vectors can be written as:

$$q_w = \begin{bmatrix} x_w \\ y_w \\ \alpha_w \end{bmatrix} \qquad \Delta q_o = \begin{bmatrix} \Delta x_o \\ \Delta y_o \\ \Delta \alpha_o \end{bmatrix}$$

Where q_w contains the webcam absolute coordinates readings, x_w and y_w, and the absolute orientation α_w. Δq_o includes the optical sensors relative coordinates readings from the most recent position measurement, Δx_o and Δy_o, and the relative orientation $\Delta \alpha_o$.

2. Checking if the new webcam data (q_w) is available.
3. Calculate fused data.
   a. A case when the next q_w is not available.

If the new q_w is not available the following equation is used to calculate the fused position and orientation:

$$q_f(t) = q_f(t-1) + \Delta q_o(t) \tag{1}$$

Where q_f is the fused position and orientation vector and t is the time step when the measurement was taken.

   b. A case when the next q_w is available.

When the new q_w is present the fused position and orientation is calculated as follows:

$$q_f(t) = q_f(t-1) + \Delta q_o(t) + wC \tag{2}$$

where w is a gain and C is a position correction term. The correction term C is calculated as follows:

$$C(t_w) = q_w(t_w) - q_f(t_w - t_d) \tag{3}$$

where t_w is the time when webcam measurements are available, t_d is a webcam data processing delay updated during each t_w time step, and q_f was interpolated at $t_w - t_d$.

To interpolate $q_f(t_w - t_d)$ 20 past measurements of q_f were stored in memory. For each iteration $t_w - t_d$ satisfies:

$$t(n-1) < (t_w(n) - t_d(n)) \leq t(n) \tag{4}$$

To minimize sudden sharp changes on a trajectory graph, rather than adding the correction term C in one t time step to correct the fused position and orientation (q_f), C was divided by 10 and added during 10 time steps t. The correction C divided by 10 was implemented over 10 steps because the minimum number of optical sensors measurements between two webcam position measurements was always greater than 10 during experimental testing.

The gain w is computed based on average strength (AS) parameters acquired by the webcam in each frame. The AS is a gradient magnitude of the tracked marker's detected edge measured from 0 to 1. The gain w was computed by multiplying together gains w_b and w_r, where w_b and w_r were separately determined for the blue (w_b) and red (w_r) markers (Figure 1b) using the following formulas:

$$\begin{gathered} w_k = 0, for AS < 0.9 \\ w_k = 6.25 \times AS - 5.125, \text{for } 0.90 \leq AS < 0.98 \\ w_k = 1, for\ 0.98 \leq \text{AS} \end{gathered} \tag{5}$$

Equation (5) was determined experimentally to filter out the noise-corrupted webcam measurements.

The simplified diagram of the proposed fusion scheme is presented in Figure 2, i is the number of correction steps.

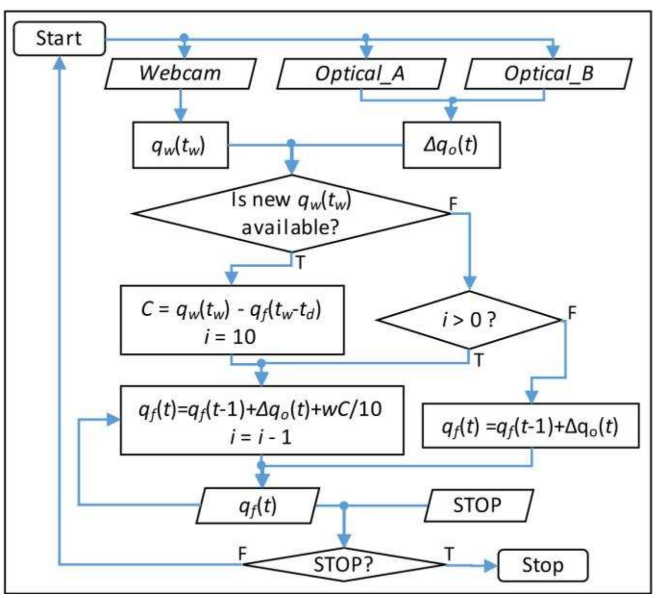

Figure 2. Simplified schematic diagram of the fusion scheme.

III. Experimental Methodology

The accuracy of the tracking system was experimentally evaluated against a reference trajectory captured at 100 Hz with Optotrak Certus motion capture system which has a measurement accuracy of approximately ±0.1mm. Figure 3 presents a diagram of the experimental apparatus utilized to collect the results. During the testing, a humanoid robotic arm, ALAN [11], developed at the University of Leeds, was used to replicate the recorded arm movements of a representative stroke patient playing a rehabilitation game. The patient trajectory data utilized was collected during a trial of the MyPAM system, an active home-based rehabilitation robot also developed at the University of Leeds [12]. A sample data set was chosen belonging to an 81 year old female who was 132 days post-stroke at the time of recruitment to the aforementioned trial. She was right arm impaired, which was also her dominant side, and she had a baseline Fugl-Meyer upper-limb assessment score of 32. The data represents the patient performing a repeated pentagram task (trying to follow a pentagram shaped trajectory for 60 seconds). In this study, 18 of the recorded 2D trajectories were tracked with the developed hybrid tracking system. As the tracked trajectories had been recorded while the patient was performing the pentagram task, the speed and range of motion was typical for rehabilitation therapy. An additional reason for selecting this patient is that she had shown clear improvement during her rehabilitation, and the question of whether the presented hybrid tracking system is accurate enough to show her therapy progress was investigated in this work.

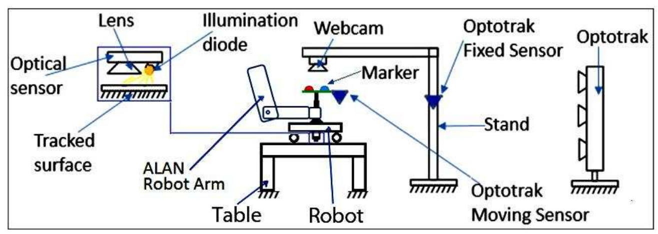

Figure 3. Schematic diagram of the experimental apparatus.

Figure 4 presents a photo taken during one of the experiments. The photo shows the ALAN robot arm moving the rehabilitation robot, which is tracked by the developed hybrid tracking system.

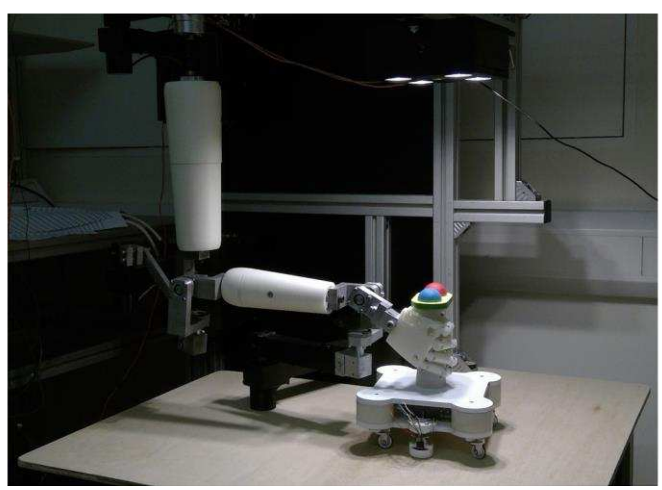

Figure 4. A photo taken during one of the experiments.

During the experiments the webcam was attached to a stand and positioned over the tracked robot covering an area of 336 by 448 mm. The resolution was set to 640 by 480 pixels, which resulted in 0.7 mm to pixel ratio. To minimize tracking errors caused by the webcam's lens distortion, a calibration algorithm utilizing a grid of dots was employed. To check the quality of acquired webcam data, three parameters were measured at each time step: blue and red marker radius (real radius is 20 mm), distance between the centers of the markers (real value is 50 mm), and AS.

IV. Experimental Results

A. Results for the webcam tracking subsystem

The average recorded frequency of the webcam was 5 Hz. Table 1 summarizes the quality measurements recorded while tracking the first pentagram assessment recreated by the ALAN robot arm. It can be noted that the detected radii for the markers by the webcam were less than the actual radii (20 mm) and are more accurate for the red maker than for the blue marker. The measurements of the distance between the markers are accurate, 50.4mm on average, which is close to the 50mm reference value. Average strength measurements indicate (similar to the marker's radii measurements) that the quality of the red marker detection was better, however all the average strength measurements are close to the 1 reference value with the minimum detected AS value equal to 0.95 and 0.97 for the blue and red markers respectively.

TABLE I. Summary of the webcam measurements. Radius of the red marker (R_R), radius of the blue marker(R_B), distance between the red and blue markers centres(D_{RB}), Average Strength of the red marker(AS_R) and the Average Strength of the blue marker(AS_B).

R_r (mm)	R_b (mm)	d_{rb} (mm)	AS_r	AS_b
19.4 (±0.2)	18.8 (±0.2)	50.4 (±0.2)	0.996(±0.01)	0.98(±0.01)

B. Results for the optical sensors tracking subsystem.

The average measured sampling frequency of the two optical sensors used was 97.2 ±17.6 Hz. To evaluate the quality of the measurements acquired by the optical sensors, surface quality measurements (Squal, measured from 0 to 169) were recorded during each t time step by the optical sensor itself. While tracking the first pentagram assesment recreated by the ALAN robot arm, the Squal measurements were 38.5 ±5.3 for the optical sensor A and 35.4 ±5.3 for the optical sensor B. These values indicate correct operation of the sensors and are similar to Squal values recorded for the smooth MDF surface presented in [8]. A smooth Plywood surface was utilized in this instance.

C. Sample results for the fusion tracking system

Figure 5 presents the XY recorded trajectories for the assessment 1 (out of 18) played by the patient.

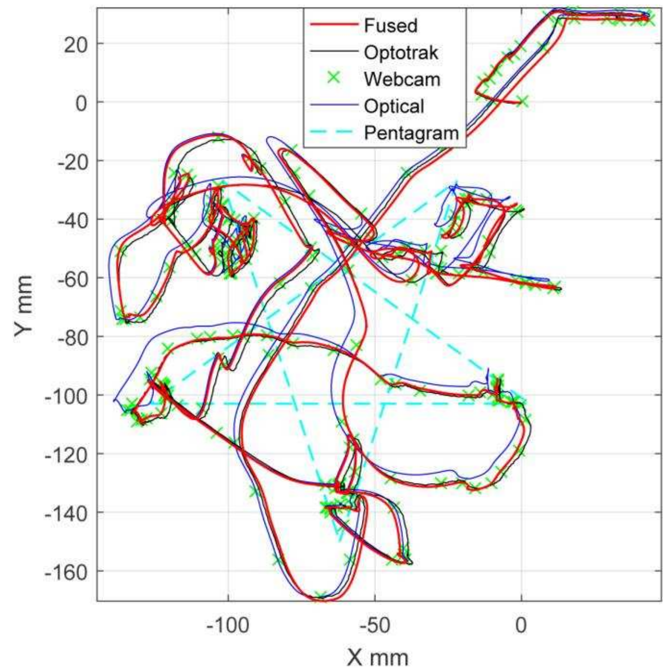

Figure 5. XY fusion graph for Fusion, Optotrak, Webcam and Optical sensor-recorded trajectories for the pentagram assesment 1 performed by the patient.

Figure 6 presents sample X, Y coordinate, and angle of rotation plotted versus time for the XY trajectory plot shown in Figure 5.

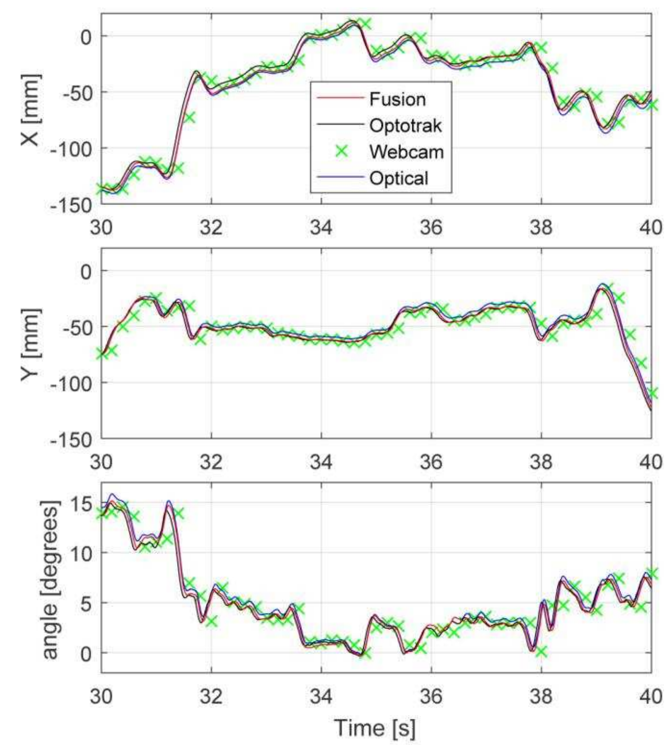

Figure 6. X, Y coordinates, and angle of rotation plots vs time (10s of 60s) for the pentagram assesment 1 performed by the patient.

D. Summary of fusion tracking results

Figure 7 summarizes the average 2D tracking and orientation accuracy of the hybrid tracking system. In both the position and orientation tracking, the calculated average RMSEs confirm that the fusion algorithm improves the accuracy by fusing data from the optical sensors and the webcam.

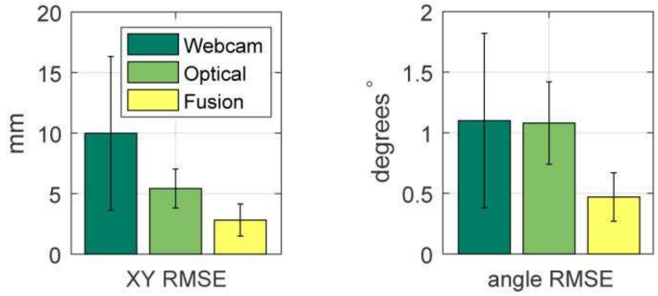

Figure 7. Average root mean square error calculated for 18 data sets for 2D XY coordinates and orientation.

E. Suitability for use in post-stroke rehabilitation therapy

To investigate the suitability of the developed tracking system for an application in upper-limb robotic rehabilitation, recovery trends for path length, path length time and normalized jerk were compared between the fusion and Optotrak recorded trajectories as presented in Figure 8. The path length is the sum of all of the component movement lengths between each point to point movement on the pentagram assessment. For each of the 18 assessments, an average length of the trajectory the patient needed to connect the vertices of the pentagram was calculated [13]. Path length time is the time the patient took to move between pentagram vertices, averaged for each of the 18 assessments. The normalized jerk is the derivative of acceleration and measures jerkiness. Jerk is used to describe smoothness of movement (it is minimized in a smooth movement) and is normalized with respect to distance and time, therefore it is unit less, so the trajectories of different lengths and durations can be compared [13].

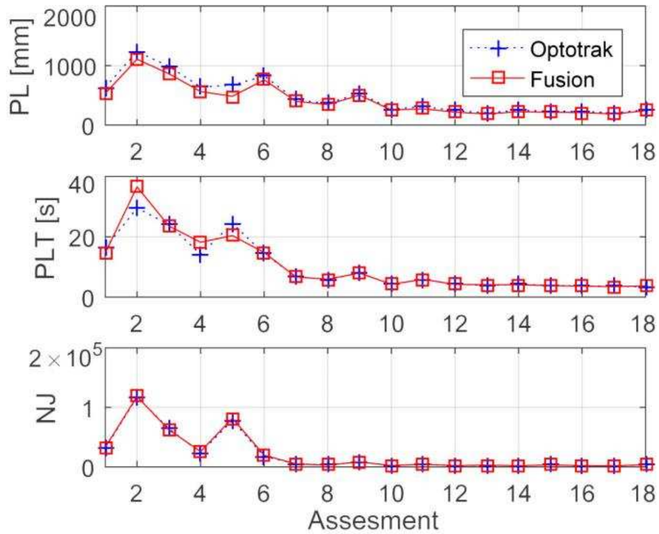

Figure 8. Path length(PL), path length time (PLT), and normalized jerk (NJ) comparision between data recorded with the Optotrak and the fusion tracking system for 18 'pentagram rehabilitation assesments' played by a post-stroke patient during 8 weeks.

The recovery trends for PL, PLT and NJ for fusion and Optotrak data plotted in Figure 8 were compared by calculating an average percentage difference for all assessment as it is presented in Figure 9. The ideal average percentage values for the fusion would be equal to 100% Optotrak reference values if they perfectly matched the recovery trends recorded by the Optotrak. Average PL, PLT and NJ data for the optical sensors and the webcam is plotted for comparison.

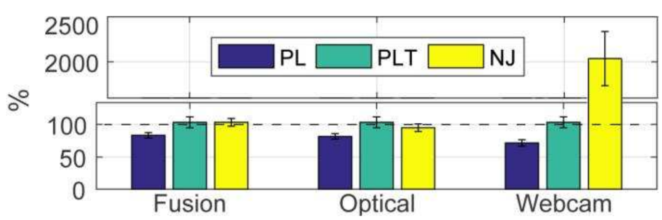

Figure 9. Path length(PL), path length time (PLT), and normalized jerk (NJ) average percentage values calculated for the fusion tracking system, the optical sensors and the webcam for all 18 assesments compared to 100% Optotrak average reference values.

V. DISCUSSION

Similarly to [8], the results comparing the RMSE (Figure 7) have confirmed that utilizing the proposed fusion scheme gives more accurate results than if the webcam and optical sensors were used alone. In this work, the functionality of the hybrid position tracking system was extended to orientation tracking and likewise in the case of the position, the orientation tracking also benefits from the fusion scheme providing more accurate orientation results.

Also, compared to the results in [8], the fusion trajectory RMS error average has improved from 6.8 ±3.4mm to 2.8 ±2.6mm, even though the webcam frame rate was lowered from 10 Hz to 5 Hz. This is due to a new calibration method being employed. It can also be noted that the average RMS error for the optical sensors-tracked trajectory has decreased compared to the optical tracked trajectory average RMS error in [8], which is difficult to explain. However, it might be caused the fact that in this study two optical sensors separated by a distance of 180mm were used together, compared to only one sensor used in [8].

As presented in [8], it has been shown that utilizing the average strength as the quality indicator of the webcam position measurements can be an effective approach to minimize the effect of noise in webcam measurements on the final fused trajectory. In future work, to minimize the changes of AS with the changes of light intensity of the scene, the markers (red and blue) can be illuminated from the inside to improve their visibility in low-light conditions.

Apart from AS, three more quality measurements from the webcam were recorded: the distance between the markers and the radii length of the markers (Table 1). It can be noted that the measurement of the distance between the markers, 50.4 ±0.2mm (where 50mm is the real world measure), and the radii measurements 18.8 ±0.2mm (blue) and 19.4 ±0.2mm (red) (where 20mm is the real world measure) are feasible considering the pixel to millimeter ratio (1pix = 0.7mm). In the future, improvements could be achieved by adjusting the settings of the color filters. However, if higher precision is needed then the best option might be increasing the resolution of the webcam.

The main requirement of the presented hybrid position and orientation tracking system is tracking the motion of the passive rehabilitation robot shown in Figure 1c. [5] has specified the global position and orientation accuracy requirements for the desktop rehab robot ArmAssist to be within ± 10 mm and ±5 deg. Their tested ArmAssist can track absolute position up to 6 ± 3 mm and orientation up to 1.2 ± 1.4 degrees. In comparison with the ArmAssist's, the proposed absolute position and orientation tracking system is more accurate, tracking 2D position up to 2.8 ±2.6mm and orientation up to 0.5 ±0.4 degrees. In the next stage of this project, a passive guiding system for the rehab robot (Figure 1b) will be developed and tested with the presented tracking system.

The feasibility of the proposed tracking system for detecting improvements during rehabilitation therapy was evaluated. The results shown in Figures 8 and 9 indicate that the hybrid system can be useful in tracking the recovery trends for the path length, path length time and normalized jerk. The percentage difference results (Figure 9) indicate that there are some inaccuracies in measuring the PL, PLT and NJ, (for fusion 90 ±5%, 102 ±10% and 102 ±7% respectively) but these should not affect the general recovery trends (Figure 8). The results in Figure 9 indicate that the webcam is not capable of tracking NJ, the average calculated value for NJ is 20 times greater than the reference value. The results in Figure 9 also indicate that the optical sensors can detect recovery trends with similar accuracy to the hybrid system. However, as the optical sensors are measuring relative position changes, they cannot be used alone.

During the experimental evaluation of the proposed hybrid position and orientation tracking system, the ALAN robot arm was used to replicate the recorded arm movements of a representative stroke patient completing assessment tasks during a rehabilitation program. Therefore, the tracked trajectories were representative of upper limb rehabilitation training in terms of their speed and range of motion.

VI. CONCLUSIONS

A hybrid position and orientation tracking system utilizing a proposed fusion algorithm was presented and experimentally evaluated. The performance was deemed to be feasible for consideration for tracking recovery trends in upper-limb rehabilitation. The system is designed to be implemented on a low-cost passive rehabilitation table-top robot suitable for therapist-independent home-based rehabilitation therapy.

REFERENCES

[1] A. Morse and A. General, "Progress in improving stroke care," London: The Stationery Office, 2010.

[2] A. Jackson, M. Levesley, S. Makower, J. Cozens, and B. Bhakta, "Development of the iPAM MkII system and description of a randomized control trial with acute stroke patients," in Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on, 2013, pp. 1-6.

[3] R. C. Loureiro, W. S. Harwin, K. Nagai, and M. Johnson, "Advances in upper limb stroke rehabilitation: a technology push," Medical & biological engineering & computing, vol. 49, p. 1103, 2011.

[4] A. Peattie, A. Korevaar, J. Wilson, B. Sandilands, X. Chen, and M. King, "Automated variable resistance system for upper limb rehabilitation," Robotics and Automation, 2009.

[5] J. C. Perry, H. Zabaleta, A. Belloso, C. Rodríguez-de-Pablo, F. I. Cavallaro, and T. Keller, "ArmAssist: development of a functional prototype for at-home telerehabilitation of post-stroke arm impairment," in Biomedical Robotics and Biomechatronics (BioRob), 2012 4th IEEE RAS & EMBS International Conference on, 2012, pp. 1561-1566.

[6] D. Luo, T. Schauer, M. Roth, and J. Raisch, "Position and orientation control of an omni-directional mobile rehabilitation robot," in Control Applications (CCA), 2012 IEEE International Conference on, 2012, pp. 50-56.

[7] J. Kowalczewski, E. Ravid, and A. Prochazka, "Fully-automated test of upper-extremity function," in Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, 2011, pp. 7332-7335.

[8] K. K. Wojewoda, P. R. Culmer, A. E. Jackson, and M. C. Levesley, "Position tracking of a passive rehabilitation robot," in Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2016 IEEE International Conference on, 2016, pp. 1-6.

[9] W. Elmenreich, "A review on system architectures for sensor fusion applications," Software Technologies for Embedded and Ubiquitous Systems, pp. 547-559, 2007.

[10] T. Nicosevici, R. Garcia, M. Carreras, and M. Villanueva, "A review of sensor fusion techniques for underwater vehicle navigation," in OCEANS'04. MTTS/IEEE TECHNO-OCEAN'04, 2004, pp. 1600-1605.

[11] J. K. Brooks, M; Kanakis, M; Grigals, A; Narvidas, MM; Gallagher, JF; Levesley, M, "Robots Testing Robots: ALAN-Arm, a Humanoid Arm for the Testing of Robotic Rehabilitation Systems," in 2017 IEEE-RAS-EMBS International Conference on Rehabilitation Robotics, London, 2017, In Press.

[12] J. Gallagher, N. Preston, R. Holt, M. Mon-Williams, M. Levesley, and A. Weightman, "Assessment of upper limb movement with an autonomous robotic device in a school environment for children with Cerebral Palsy," in Rehabilitation Robotics (ICORR), 2015 IEEE International Conference on, 2015, pp. 770-774.

[13] P. R. Culmer, M. C. Levesley, M. Mon-Williams, and J. H. Williams, "A new tool for assessing human movement: the kinematic assessment tool," Journal of neuroscience methods, vol. 184, pp. 184-192, 2009.