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Sensor Fusion of Leap Motion Controller and Flex Sensors using Kalman Filter for Human Finger Tracking

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ABSTRACT

In our daily life, we, human beings use our hands in various ways for most of our day-to-day activities. Tracking the position, orientation and articulation of human hands has a variety of applications including gesture recognition, robotics, medicine and health care, design and manufacturing, art and entertainment across multiple domains. However, it is an equally complex and challenging task due to several factors like higher dimensional data from hand motion, higher speed of operation, self-occlusion, etc. This paper puts forth a novel method for tracking the finger tips of human hand using two distinct sensors and combining their data by sensor fusion technique.

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1. INTRODUCTION

Over the course of years, extensive research has been conducted to exploit many possible technologies to achieve the common objective of human hand tracking. The systems in place can be preliminarily classified as vision based and non-vision based tracking systems. Vision based tracking uses cameras [1-5] or other optical devices like the Kinect sensor [6-9], Leap motion controller [10-12], etc., whereas non-vision based systems often use wearable interfaces [13–16] to estimate the position and orientation of the hand.

Both the systems have their own advantages and disadvantages with some more suited for certain applications. The vision based system offers nil or minimum interference to the user. They are free from cumbersome wiring allowing the individual to perform the hand motion in the most natural way possible. However, the quality of tracking will be greatly affected by external environmental factors like ambient light, objects in the tracking area with similar color and/or shape, etc. They are also poorly guarded against the problem of Occlusion – where the line of sight to the objects being tracked is blocked. On the other hand, non-vision based systems are completely neutral to these problems. However, they will not be able to provide exact 3D co-ordinates of the finger tips and need to be calibrated to prevent accumulation of errors. They also add on additional hardware which may cause discomfort to the user for prolonged use.

The objective of this paper is to exploit the advantages of both the methods to achieve a superior tracking method. The sensors taken into consideration are the Leap motion sensor (vision based tracking) and the Flex sensor (non-vision based tracking). In this paper a novel strategy is proposed in combining these two sensors. The key contribution will be the usage of sensor fusion algorithm for tracking finger level data based on the inputs from both the sensors. The effects of occlusion and environmental noise in the form of ambient light in tracking performance can be minimized, thus increasing the accuracy and reliability of tracking.

In the following sections, the design, working and experimental results of the proposed Sensor fusion method are discussed. In Section II, various types of sensor fusion methods are briefly described. In Section III, a brief description of the two sensors under study is given. In Section IV, basic Kalman filter is discussed from sensor fusion point of view. The model equations and parameters of the Kalman filter for the problem of finger tip position tracking are derived. In Section V, the experimental setup is explained and the results are discussed which is followed by remarks and conclusions in the subsequent section.

2. RELATED WORK

Sensor fusion denotes the process of combining the data from separate sources to produce a common data that has improved accuracy and reliability than each of the sources individually. A natural example of sensor fusion can be seen in Human vision where inputs from both our eyes are combined to project a single image by the occipital center of the brain. Sensor fusion is often realized in software that compensates for the deficiencies of the individual sensors.

Research on sensor fusion methods has been started as early as 1980s [17, 18]. The most common methods in recent times use a Bayesian state estimator like a Kalman filter or a Particle filter to calculate a single fused state from different sensors. In general, the sensor fusion algorithms can be roughly classified into three categories based on the way they handle the correlation among the data from the different sensors. The first category assumes there is no prior knowledge on the correlation. Common examples include the Covariance intersection algorithm [19] and the Ellipsoidal intersection algorithm [20]. However, these methods are computationally complex and the error covariance of the fused data estimate is not proven to be smaller than that of individual sensor data estimates in most of the cases.

Under the second category, the correlation is calculated based on the individual sensor values (as in Information Matrix Fusion algorithm [21]) and model parameters of the individual sensor systems (as in Cross-Covariance Method [17]). The third and final category algorithms assume that the correlation is known either partially [22] or fully [23].Kalman filter falls under the second or third category depending on the sensor systems used and the correlation between them. The advantage of this algorithm is that it improves the estimation accuracy of the fused state and is better than that of individual sensor estimates.

3. SYSTEM DESCRIPTION

The system comprises of two input devices – Leap motion controller (LM) and Sensorized glove (SG) made using Flex sensors. The objective is to combine the input from both the sensor systems to produce a single reliable finger tip position data.

The LM is able to track the finger tip positions with high accuracy in most of the cases. The major drawback is the problem of occlusion. Whenever the LM cannot visibly see a part of the hand, it makes assumptions based on the data available and an understanding of how the human hand works. However, in such cases the finger tip positions are often predicted wrongly making it less reliable for critical applications. This particular problem of LM can be overcome by combining it with the SG since the latter does not require direct line of sight for operation. The overall block diagram of the system is given in Figure 1.

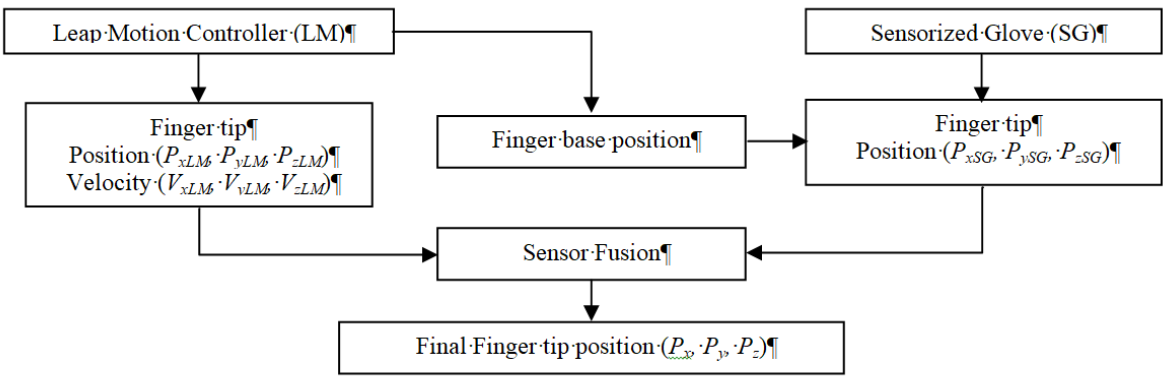

Figure 1. Overall System structure

3.1. Leap Motion Controller

Leap Motion controller is a motion sensor specifically designed to track human hands. The device is tiny (approx. 79 x 30 x 11mm) and operates in an intimate proximity with high precision and tracking frame rate (20 to 200 frames per second depending on the user's settings available computing power). It uses two infrared cameras (sensors) and three infrared LEDs [24]. The grayscale stereo image data as seen by the sensors are sent to the PC, where advanced algorithms (not disclosed by Leap motion Inc.) are employed to extract three dimensional data. The sensors have about 150 degrees field of view and an effective range of approximately 0.03 to 0.06 meters above the device.

Even though the manufacturers have claimed an accuracy of 0.01mm in position measurement, research [25] shows that it is actually around 0.2mm and 0.4mm for static and dynamic measurements respectively. In a similar research [26], repetitive measurements were taken to test the precision of the device. The maximum standard deviation was found to be less than 0.5mm making it a reliable and accurate device for tracking. The major drawback of Leap motion controller is the problem of self-occlusion. One hand covering another, movements of the fingers when the hand is upside down or sideways when multiple fingers curl or come together are some cases where the problem of self-occlusion occurs.

3.2. Sensorized Glove-Flex Sensors

Flex sensors are analog input devices whose resistance changes when they are bent by external force. They can be used to detect flexion/extension of a Human finger. By mounting them above the fingers and using a simple voltage divider circuit, the amount of flexion can be measured as they bend along with the finger. Even though Human hand has more than 20 DOFs, it cannot assume any arbitrary position due to certain anatomical and biomechanical constraints. Referring to Figure 2, the following constrains were put forth in [27].

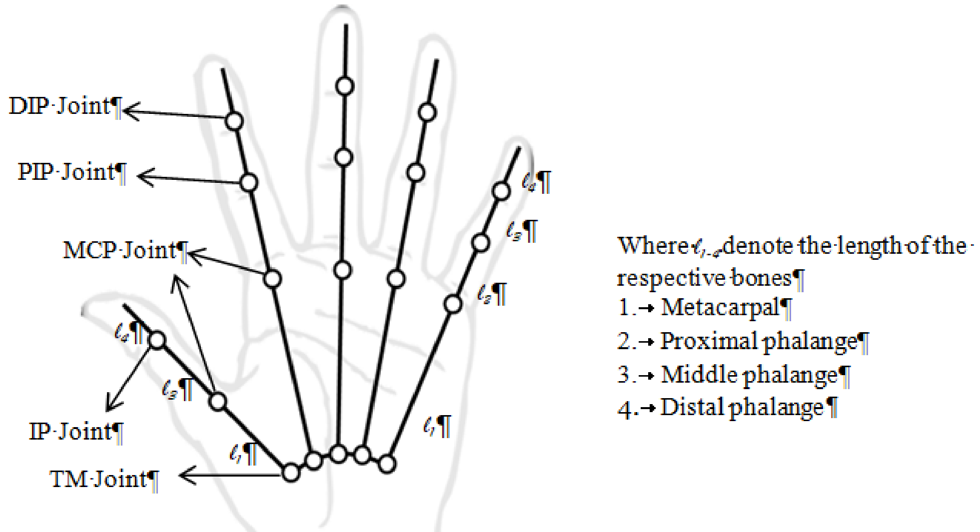

Figure 2. Human hand showing the joints and bones

For general finger model (1-2):

$$\theta_{DIP} \approx \frac{2}{3}\theta_{PIP} \tag{1}$$

$$\theta_{PIP} \approx \frac{3}{4}\theta_{MCP,f/e} \tag{2}$$

For thumb model (3):

$$\theta_{IP} \approx \frac{1}{2}\theta_{MCP,f/e} \tag{3}$$

The suffix MCP, f/e is to distinguish the flexion/extension angle from the abduction/adduction angle at the MCP joint. In addition to the above constraints, it is also noted that the flexion movement of the finger is similar to a planar manipulator. Thus, the one-dimensional data obtained from the flex sensor, along with the above constraints, can be used to estimate the joint angles of the fingers. The relative position of finger tips, with respect to the position of finger bases, can be obtained by substituting the joint angles in forward kinematic equations written based on Denavit-Hartenberg (D-H) convention. However, this method cannot give the precise location of the finger tip in a three dimensional space. Hence exact 3D position is obtained by superimposing the relative finger position over the finger base position from the Leap motion controller.

For the experiments and discussions in this paper, a simple arrangement was made as follows. Three flex sensors were stitched along the outer-dorsal surface of a glove, one each for the thumb, index and middle fingers. A voltage divider circuit was attached to the back of the hand and the data was fed to the PC through an Arduino microcontroller kit. This setup will be henceforth called as the Sensorized Glove (SG) in the remaining of the script. This method is relatively cheaper than other glove based tracking methods using accelerometers or mechanical attachments.

4. SENSOR FUSION – KALMAN FILTER

Out of the various methods of sensor fusion described in Section II, Kalman filter is chosen for the application. It is a recursive algorithm which can be used in sensor fusion applications due to its ability to estimate the auto-covariance values within a source of measurement. It is hence able to produce a fused state of output from n different sensors with minimum covariance possible [28]. For the system in hand, the outputs available from various sensors are position (pxLM, pyLM, pzLM) and velocity (vxLM, vyLM, vzLM) from LM and position (pxSG, pySG, pzSG) from the SG. Consider the following state-space model of a linear time-invariant system in discrete domain (4),

$$\begin{cases} x_k = \Phi_k . x_{k-1} + \Gamma_k . u_{k-1} + b_{k-1} \\ \qquad z_k = H_k \cdot x_k + v_k \end{cases} \tag{4}$$

where b_k and v_k denote process noise and measurement noise respectively. The system output z_k is given by (5),

$$z_k = [p_{xLM}\ v_{xLM}\ \ p_{yLM}\ \ v_{yLM}\ \ p_{zLM}\ \ v_{zLM}\ \ p_{xSG}\ p_{ySG}\ p_{zSG}]^T \tag{5}$$

Since there are no external sources of influence in the human hand motion, the system input u_k can be assumed as zero. The system states at any instance *k* are given by (6),

$$x_k = [p_{x|k}\ v_{x|k}\ \ a_{x|k}\ \ p_{y|k}\ \ v_{y|k}\ \ a_{y|k}\ \ p_{z|k}\ v_{z|k}\ a_{z|k}]^T \tag{6}$$

where *'p'*, *'v'* and *'a'* denote the position, velocity and acceleration along the respective axes. Hence the Observation matrix relating the states and output becomes (7),

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \tag{7}$$

The first six rows of the matrix correspond to LM measurement where as the last three rows are for the data from SG. The direction cosine matrix relating the hand coordinate axes and the world coordinate axes is given by (8),

$$M_{HW} = \begin{bmatrix} m_{X_x} & m_{Y_x} & m_{Z_x} \\ m_{X_y} & m_{Y_y} & m_{Z_y} \\ m_{X_z} & m_{Y_z} & m_{Z_z} \end{bmatrix} \tag{8}$$

where $m_{X_x} = \cos\theta_{i_j}$ and θ_{i_j} denotes the angle between the *i*-axis in the hand frame and the *j*-axis in the world frame. According to linear equations of motion, the relation between position, velocity and acceleration are given by (9-10),

$$v_x = \dot{p_x};\ v_y = \dot{p}_y\ ;\ v_z = \dot{p}_z \tag{9}$$

$$\begin{cases} \dot{v}_x = m_{X_x}.a_x + m_{Y_y}.a_y + m_{Z_y}.a_z \\ \dot{v}_y = m_{X_y}.a_x + m_{Y_y}.a_y + m_{Z_y}.a_z \\ \dot{v}_z = m_{X_z}.a_x + m_{Y_z}.a_y + m_{Z_z}.a_z \end{cases} \tag{10}$$

Hence, for a sampling time t, the state transition matrix Φ_k relating the current and previous states is derived as (11),

$$\Phi_k = \begin{bmatrix} 1 & t & m_{X_x}.t^2/2 & 0 & 0 & m_{Y_x}.t^2/2 & 0 & 0 & m_{Z_x}.t^2/2 \\ 0 & 1 & m_{X_x}.t & 0 & 0 & m_{Y_x}.t & 0 & 0 & m_{Z_x}.t \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & m_{X_y}.t^2/2 & 1 & t & m_{Y_y}.t^2/2 & 0 & 0 & m_{Z_y}.t^2/2 \\ 0 & 0 & m_{X_y}.t & 0 & 1 & m_{Y_y}.t & 0 & 0 & m_{Z_y}.t \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & m_{X_z}.t^2/2 & 0 & 0 & m_{Y_z}.t^2/2 & 1 & t & m_{Z_z}.t^2/2 \\ 0 & 0 & m_{X_z}.t & 0 & 0 & m_{Y_z}.t & 0 & 1 & m_{Z_z}.t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{11}$$

Assume process and measurement noises to be white noises with probability density functions as (12),

$$\begin{aligned} &p(b) \sim N(0, Q) \\ &p(v) \sim N(0, R) \end{aligned} \tag{12}$$

where Q and R represent the process noise covariance and measurement noise covariance respectively. The sequential steps of Kalman filter, in each iteration, are as follows (13-16).

1 *a priori* covariance estimation:

$$P_k = \Phi_{k-1}P_{k-1}[\Phi_{k-1}]^T + \Gamma_{k-1}Q_k[\Gamma_{k-1}]^T \tag{13}$$

2 Kalman gain calculation:

$$K_k = P_k[\mathrm{H}_{k-1}]^T\{\mathrm{H}_{k-1}P_k[H_{k-1}]^T + R_k\}^{-1} \tag{14}$$

3 State estimation:

$$\hat{x}_k = \Phi_{k-1}\hat{x}_{k-1} + K_k[z_k - H_k\hat{x}_{k-1}] \tag{15}$$

4 *a posteriori* covariance estimation:

$$\hat{P}_k = [I - K_kH_k]P_{k-1}[I - K_kH_k]^T + K_kR_k[K_k]^T \tag{16}$$

The position P ($p_{x|k}$ $p_{y|k}$ $p_{z|k}$) from the newly estimated state at instance k denote the final position as a result of the sensor fusion.

5. EXPERIMENTS AND RESULTS

In order to prove the superiority of the proposed method, the following experiments were conducted. Finger tip positions of index, middle and thumb fingers during selected hand gestures were measured both from LM alone and from the sensor fusion method.

The Sensorized Glove (SG) is worn by the user on the right hand and the gestures are performed over the Leap Motion controller (LM). Figure 3 shows the system components in the experimental setup. The proposed sensor fusion using Kalman filter Equatin 13-16 is realized in software using Unity and Visual C#. The final output is displayed in a simulated 3D environment as a visual feedback to the user. The values are also stored separately in a file and are used later for analysis and plotting. All measurements used in the analysis denote the finger tip positions with respect to the center of the right palm. The ground truth is measured in parallel using Electromagnetic trackers (Ascension Technology Corporation) attached to the finger tips and the palm center.

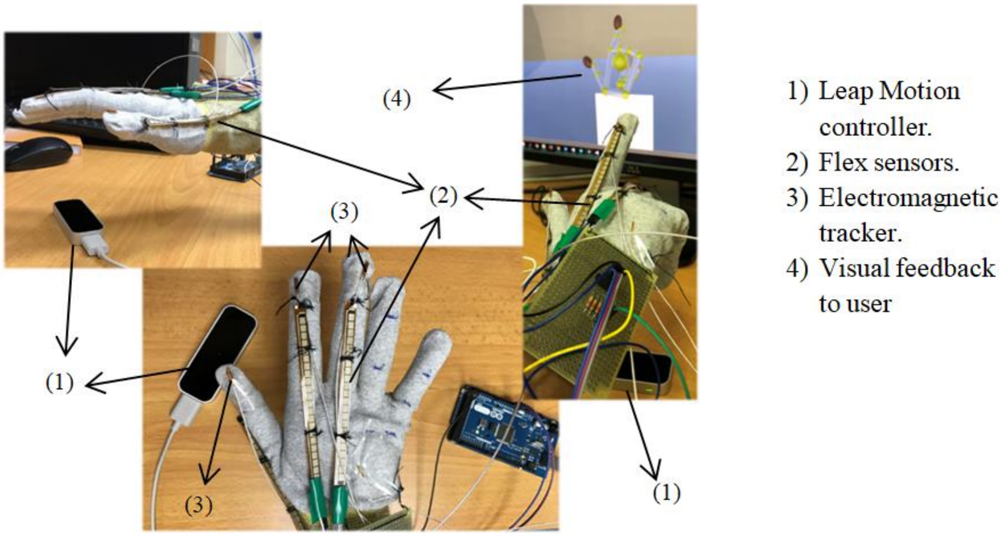

Figure 3. System components in experimental setup

Four static postures were selected from [29] that can show the problem of self-occlusion evidently during LM tracking. Initially, the posture was kept facing the LM and later, the hand was re-oriented to face away from the LM. Error was calculated as percentage deviation with respect to the ground truth measured by the electromagnetic trackers. Figures 4-7 shows the comparison of root mean square (RMS) errors of the proposed sensor fusion method (blue) with those of LM alone (red). Each graph comprises of three insets representing the three fingers being tracked–thumb, index and the middle finger respectively except the tip pinch gesture as shown in Figure 7 where the middle finger was not tracked.

When the gesture is performed with palm facing up (away from the view of the LM), one or two fingers are occluded by the palm. During occluded cases, the LM estimates the position of the finger based on the previous data and some basic knowledge on human hand behavior [24].

5.1. Sphere Formation With Three Fingers

The Sphere formation with three fingers is a static gesture that comes under the category of thumb abducted power grasp. The thumb, index and middle fingers assume a position which can hold a spherical object between them inset in Figure 4. When the orientation is reversed so that the palm faces away from the LM, the middle finger is entirely occluded by the back of the hand and the index finger is partially occluded. Hence the Leap motion controller was not able to estimate the position of the finger tips accurately. While the initial orientation had similar error values for both the methods, the error values of the final orientation were almost reduced to half by the proposed sensor fusion method as shown in Figure 4.

5.2. Parallel Extension

The Parallel extension denotes the extension of the thumb in parallel to the other four fingers. The thumb lies in a position between abduction and adduction. When the orientation is reversed, the thumb is entirely occluded by the palm. The proposed method is able to reduce the error percentage of thumb position from 4% to 2% as shown in Figure 5 a slight improvement in position of the other two fingers can also be observed.

5.3. Fixed Hook Grasp (‘OK’ Sign)

The fixed hook grasp is similar to the ‘OK’ sign as shown in the inset of Figure 6. The thumb will face directly towards the LM during the first orientation and directly away from it in the reversed orientation where it was entirely occluded by the side of the hand. The proposed sensor fusion method is able to overcome this drawback and reduce the error percentage to less than 1% as shown in Figure 6.

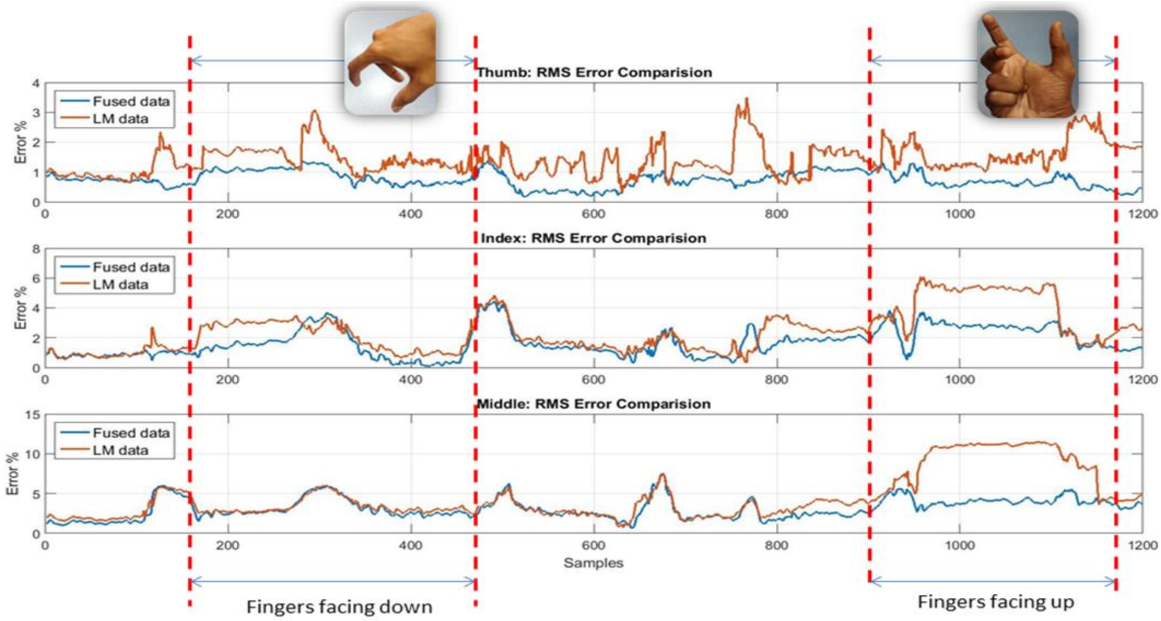

Figure 4. Comparison of RMS errors of LM alone and the proposed Sensor fusion method for 3 finger sphere formation

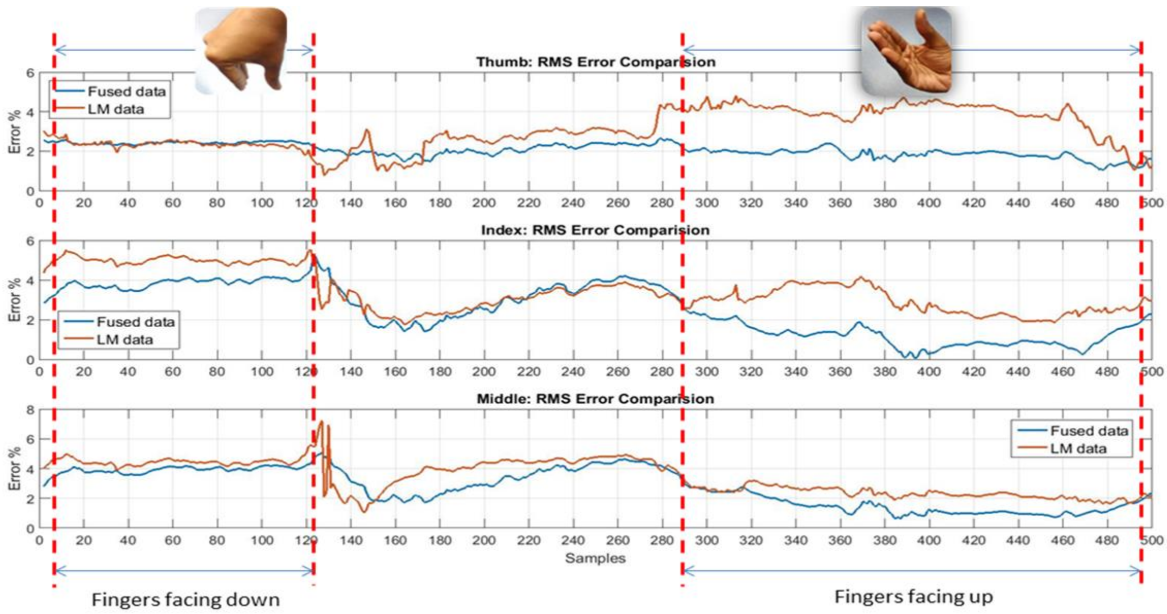

Figure 5. Comparison of RMS errors of LM alone and the proposed Sensor fusion method for Parallel extension

5.4. Tip Pinch

The tip pinch posture is achieved by joining the tips of the thumb and the index finger. The remaining three fingers may assume any relaxed arbitrary position. With the palm facing away from the LM, the thumb and index fingers are entirely occluded by the back of the hand. An interesting observation found during this posture is that the LM estimates the position of the occluded index finger tip correctly for a brief period of time as shown in Figure 7. However similar results were not found when the experiment was repeated. Hence it can be concluded that the estimate made by LM is temporary, unreliable and often contain significant errors. On the other hand, the proposed method is able to achieve lesser error percentage with a constant and reliable output. The improvements in the error percentage for the various postures are consolidated in Table 1.

Table 1. Error Comparison between LM and Sensor Fusion method

Posture	Sphere formation 3 fingers		Parallel Extension	Fixed hook grasp	Tip Pinch	
Finger	Index	Middle	Thumb	Thumb	Index	Thumb
LM error	5%	10%	4%	4%	4~10%	4%
Sensor Fusion error	<3%	4%	2%	<1%	1~5%	<3%

Remarks: All experiments were conducted indoors with no other IR sources near the leap motion controller.

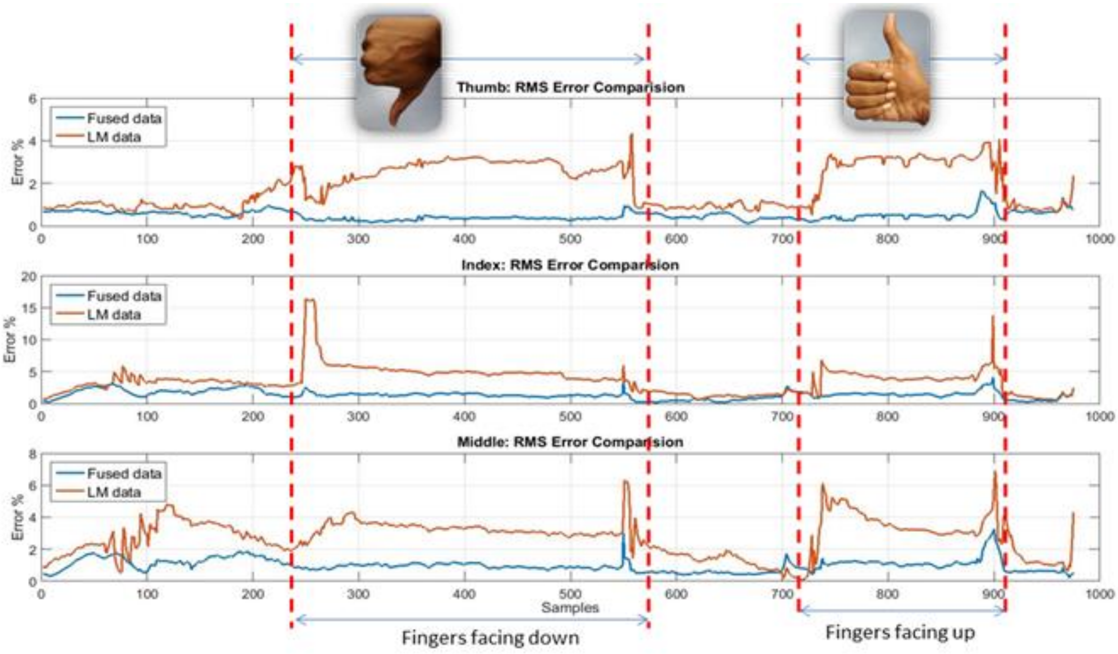

Figure 6. Comparison of RMS errors of LM alone and the proposed sensor fusion method for fixed hook grasp (OK sign)

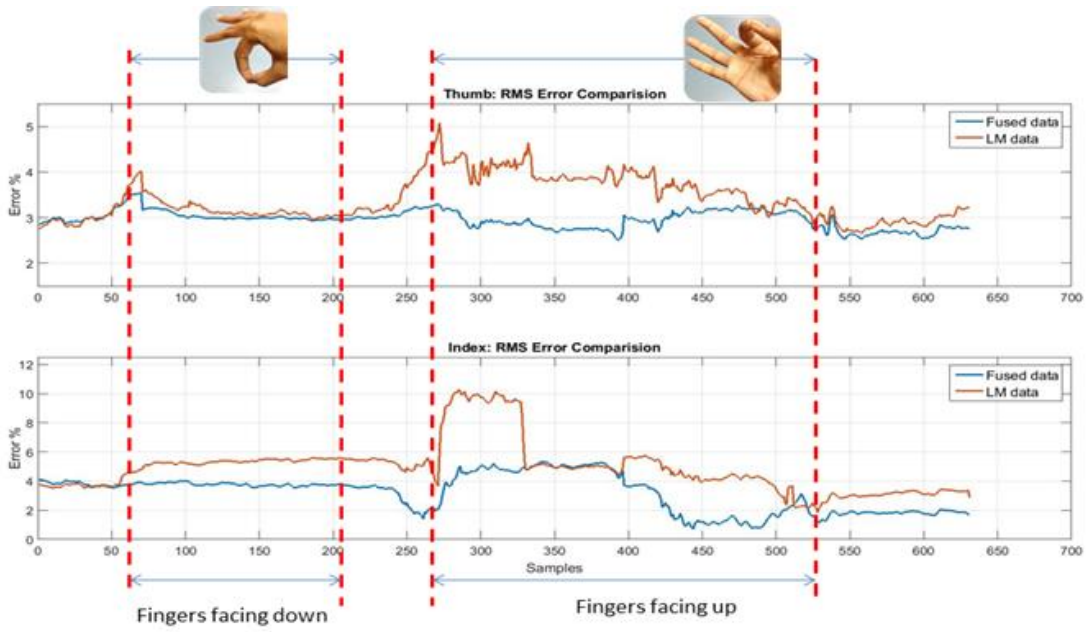

Figure 7. Comparison of RMS errors of Leap motion alone and the proposed Sensor fusion method for Tip pinch

6. CONCLUSION

The Leap motion controller is an excellent input device that tracks the movement of the Human hand. However, like any other vision based tracking device, it suffers from the problem of occlusion. In this paper, a method to overcome this drawback is discussed. By combining the leap motion control with a simple non-vision based finger tracking system (Sensorized Glove), the accuracy of tracking is improved in occluded cases. Kalman filter was used to fuse the data from the two sensors to produce a combined output with minimum least square errors. Experiments were conducted and the results were compared with original LM tracking.

Even though in some cases the LM estimation proves to be accurate as seen briefly in the Tip pinch posture as shown Figure 7, it is temporary and often unreliable with significant errors. The proposed sensor fusion method has been proved to reduce the error in occluded scenarios thus increasing the overall accuracy and reliability of the device. Future work can be done to extend this method to incorporate joint angle and orientation data of each bone from the LM and with the help of multiple flex sensors to further reduce the error percentage.

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