A Preliminary Investigation into Infrared Sensors in Wearables for Upper Extremity Motion Sensing

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***Abstract*—Studies demonstrate that monitoring and recording movement of rehabilitation exercises can improve the degree of recovery of the patient. Technologies exist to track user movements but they are often large, expensive, or require multiple units to be mounted on the user in different locations. Each of these can be barriers to patient adoption of rehabilitation technologies inside the home. We propose a single unit which incorporates an inertial measurement unit (IMU) and infrared sensors to determine orientation of the arm for various movements. The infrared sensors compensate for IMU drift errors, providing a sensor fusion solution. A novel optical wearable was created for detection of arm movement exercises in three-dimensional space that are consistent with stroke survivor exercises for spasticity rehabilitation. A study of five participants yielded high average accuracies of 98% across participants, without requiring any normalization of results to varying body sizes of participants. These findings indicate a strong inter-patient similarity in arm movement patterns. This inter-patient similarity implies the possibility of a transfer learning application, where various patient data can be used to collectively improve the accuracy of the predictive machine learning model. This could allow development of a medical device that is easily donned by the user for rehabilitation in the comfort of their own home, allowing more effective telerehabilitation.**

Keywords—Rehabilitation; stroke; spasticity; telerehabilitation; telerehab; rehabilitation devices; medical devices; wearable technology; biomedical engineering; machine learning; physical rehabilitation; wireless technology; optical sensing; sensor fusion; transfer learning

I. Introduction

Motion sensing and motion capture has applications in several industries, including medical, sports, and entertainment. Motion capture can be used in the entertainment industry to capture a person's limb movements or facial expressions and map these motions to a digital animation. Motion capture for sport or medical industries focuses on capturing the movement of an individual to enable precise analysis of user movements. While several high-accuracy motion capture systems exist, many of them command a high sales price and require a trained professional to operate them. Price and a trained operator may not be an impediment in professional sport teams and private health clinics, but are a barrier to technology adoption in home-based rehabilitation [1], where a user would typically rent or purchase hardware to aid rehabilitation and may only be supervised intermittently by a clinician.

Stroke is one such medical condition that affects over 15 million people annually worldwide. It is the fifth leading cause of death in USA. Survivors of a stroke frequently suffer from a condition called spasticity, which limits their strength, range of movement, and overall independence [2].

It is generally recognized that the extent of a stroke patient's recovery can increase with the degree rehabilitation they receive [2]. Technologies that allow monitoring of patient exercises while at home (telerehabilitation) are considered a crucial part of extending patient rehabilitation [3], [4]. Studies have demonstrated improved physical function in individuals who undergo telerehabilitation when compared to usual care [5].

A. Existing Wearables for Motion Sensing

Significant research has been done into designing wearable technologies for rehabilitation motion sensing. Designs frequently incorporate an inertial measurement unit, or IMU, which provides accelerometer, gyrometer, and magnetometer data. Integration of gyroscope data and double integration of accelerometer data allows determination of position and orientation of the device and user.

If these IMU sensors are placed on multiple points of the body, the combined orientation values can be used to reconstruct the movement path of a limb in free space. Many studies have been completed on systems which incorporate multiple IMU systems for limb orientation and position tracking [6], [7]. These systems situate the IMUs at different places on the body such as wrist, elbow, shoulder, and back. Motion tracking within 2 cm accuracy has been achieved with multi-unit systems, however, the systems are difficult to don without assistance [8]. Difficulty donning the device can be a barrier to user acceptance of the device.

Very few studies have used single IMU for upper extremity motion sensing. Some studies have used single IMU systems to provide motion classification between broad classes of movements, which can include arm and leg movements [9]. Single IMU systems for arm position estimation often incorporate a maximum likelihood estimate (MLE) of the arm position based on possible location data from the single IMU. The position estimates are constrained by the limitations on possible anatomical positions, but full estimation of arm orientation and position is difficult because of the 7 degrees of freedom of the human arm [10]. Error values are higher with single IMU systems, with errors of 9-13 cm being reported [11].

In both multi-sensor and single-sensor IMU motion tracking systems, drift of the IMU sensor is a recognized challenge [12], since repeated integration of sensor data can propagate signal noise and accumulate error over time. We propose incorporating additional sensors into the device to reduce effects of sensor drift, improving accuracy of a device having prolonged usage. Incorporating additional sensors to compensate for IMU drift can be considered a form of sensor fusion, whereby the additional sensor data can improve performance and accuracy of the system.

Our prior work [13] demonstrated the initial feasibility for such a device, incorporating passive infrared (PIR) sensors and active IR sensors in addition to the IMU. This device could classify 3 different dynamic arm movements correctly with 88% accuracy. Only one study was found which used infrared sensing technology, but this was incorporated as a goniometric rotary encoder [14]. A literature review did not yield any other publications which utilize infrared sensors for direct sensing of the user's movements [15].

II. MATERIALS AND METHODS

An updated device was created, incorporating additional PIR and active IR sensors to increase the field-of-view (FOV) of the device (Fig. 1). The layout of the sensors has been offset at angles from the transverse (horizontal) plane to increase the FOV of the device at different levels of pronation and supination. This device is a wrist wearable device containing an IMU, and four PIR and four active IR sensors. Sensor data is processed by an Arduino Pro Mini microprocessor and sent via Bluetooth connection to a computer. The unit is portably powered by a lithium polymer battery. The completed unit can be seen in Fig. 2.

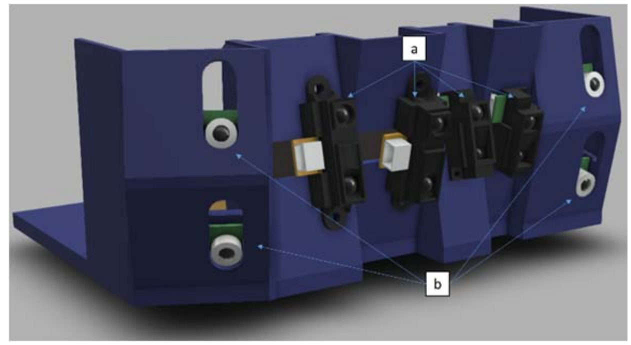

Fig. 1. Concept model of device. (a) Active IR sensors; (b) Passive IR sensors.

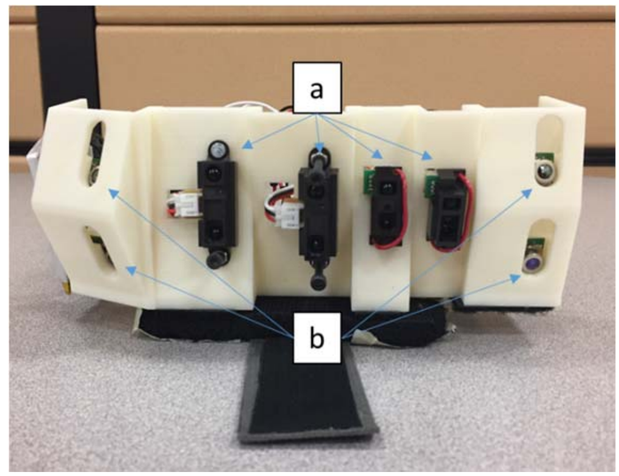

Fig. 2. Optical wearable device. (a) Active IR sensors; (b) Passive IR sensors.

1) *Active IR*

The active IR sensors emit a safe infrared light which is received by a photodiode on the unit. The time of flight (TOF) between transmission and reception or phase change of the received signal is used to determine the distance from emitter to nearby objects. The sensor outputs a voltage reading proportional to the distance of nearby objects.

2) *Passive IR*

Passive IR sensors were chosen that are selectively sensitive to thermal emissions in the Longwave IR region (LWIR), allowing human thermal emissions to be detected. These particularly PIR sensors contain an array of sensors, meaning that the presence and direction of a person can be sensed based on pixels that appear "warmer".

The Arduino receives the sensor data, formats and transmits via Bluetooth connection to a computer. Data is received into a LabVIEW program where the data is saved to a CSV file. Results are then analyzed offline with Python machine learning code.

III. Experimental Protocol

A. *Exercise Protocol*

We designed an exercise protocol to demonstrate the device's ability to determine orientation of the wrist relative to the user's torso, and the distance of the wrist from the user's torso.

Participants were guided to complete arm movements at varying distances along five axes relative to the user: forward, left, right, upwards, and downwards. These trials were conducted with the device mounted on the left wrist.

The five axes have a common origin point near the user's left shoulder. Users completed gestures in the left, right, upward and downward axis by moving their hand 10 cm, 25 cm, or 40 cm from the center resting position at the origin point. Movements along the forward axis were completed in 5 cm intervals from 15 – 60 cm. Movement along each axis can be seen below in Fig. 3. The total number of completed movements is 22.

A test area was prepared to guide user movements. Specific distances are delineated on a paper track in the test area. The user sits so that the forward axis aligns with their left shoulder. Users complete these exercises while seated at a table (Fig. 4).

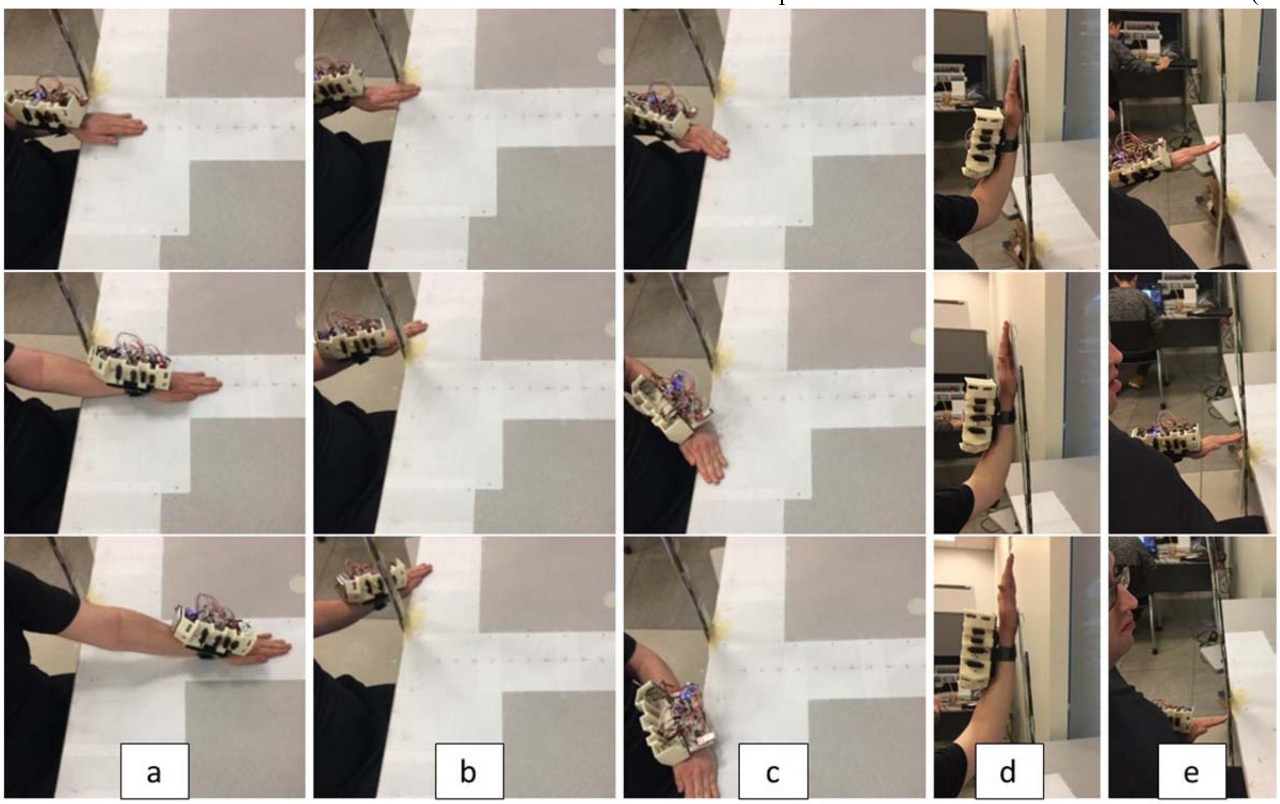

Fig. 3. User movements along 5 axes. (a) Forward axis; (b) left; (c) right; (d) upwards; (e) downwards.

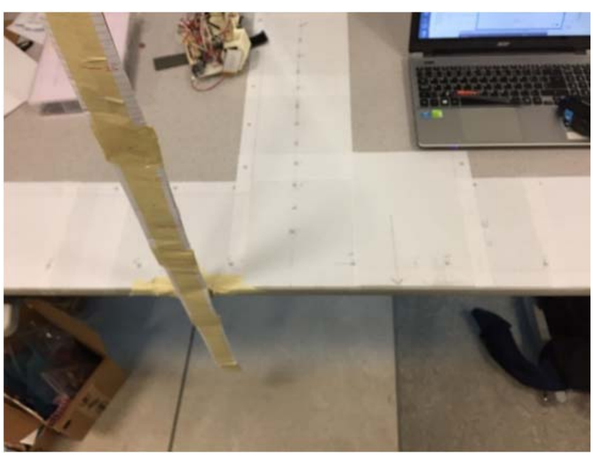

Fig. 4. Test area for trials.

B. *Experimental Procedure and Data Recording*

Participants completed 10 repetitions of the 22 gestures, for a total of 220 acquisitions. A test supervisor was present to brief the participant, aid the participant in donning the device, and initiate data recordings.

Data was recorded through use of a National Instruments LabVIEW Graphical User Interface (GUI) which received data wirelessly from the device via Bluetooth connection. Data was transmitted from the device at a 10 Hz frequency and received by the LabVIEW program, which sent the results to a file for the specific patient, gesture, and repetition. Each individual acquisition was a minimum of 1 second in length. The average time to complete 220 acquisitions, including setup and rest periods was about 30 minutes.

C. Machine Learning Analysis

Data was analyzed using Python Machine Learning software. A Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel was used.

A total of 55 features were used for the analysis, and can be summarized as follows:

- Three features (yaw, pitch, and roll) come from the orientation data from the IMU.
- Four features from the active IR distance sensors.
- Forty-eight features from the array PIR sensors.

Prior to machine learning analysis, data values were feature scaled to ensure equal weighting of each feature in the analysis. Data was normalized across all participants to have a mean of zero and a standard deviation of 1. Data was then segmented into testing and training data. The machine learning model learned with the training data, and then accuracy was assessed using the unseen testing data. The model was cross validated 25 times by randomly shuffling the data for repeated analysis, and taking the average of the results.

A meta-analysis indicated that data accuracy is not strongly affected by the proportion of data segmented for testing and training, Fig. 5. Accuracy values were very high for most testing/training fractions, and accuracy only decreased for scenarios where more than 80% of data was reserved for testing, which is a generally unrealistic scenario. It was chosen to segment 20% of data for testing, and 80% for training.

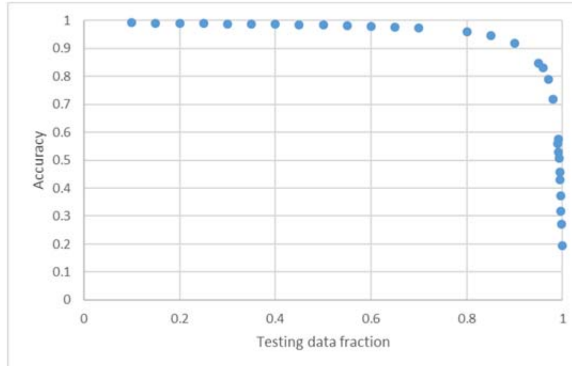

Fig. 5. Model accuracy as a function of testing/training data segmentation.

IV. RESULTS

High overall accuracies of 98% were reported from the machine learning model. The accuracy levels for each movement gesture are summarized in a confusion matrix in Fig. 6. The confusion matrix shows the gesture that the machine learning model predicts for each of the labeled test data samples. An accurate model shows highest values on the diagonal, corresponding to a model with high prediction accuracy. Our analysis indicates that model accuracy is very high for most classes. Note that the movements on different axis are labeled with a letter for the axis, and a number for the distance. "L1" is a left axis movement with 10 cm displacement from the torso. "R2" is a right axis movement with 25 cm displacement. "U3" is an upward reaching movement with 40 cm displacement.

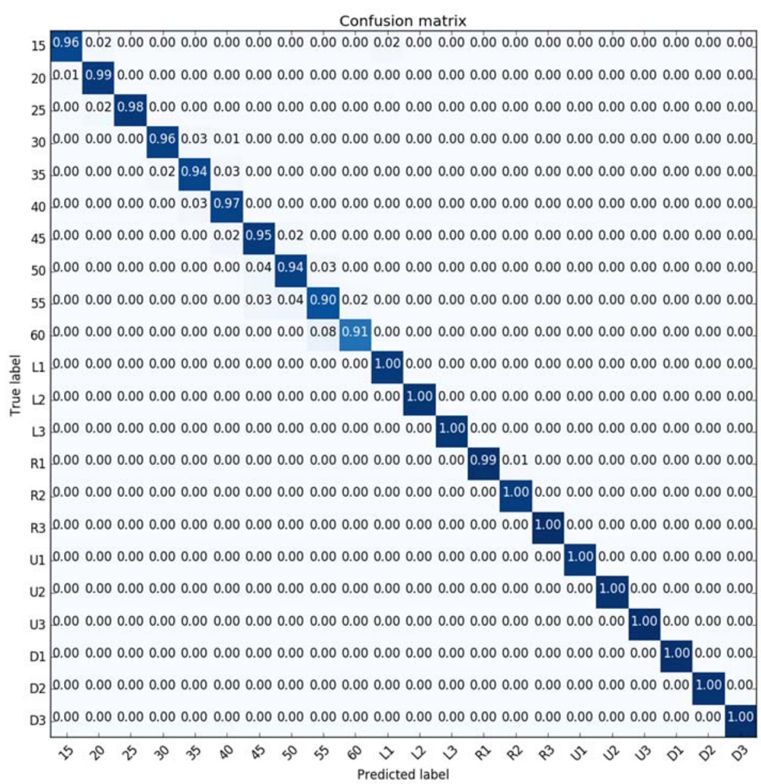

Fig. 6. Confusion matrix.

Note that this analysis tested the model's accuracy at predicting the position of the user's wrist in space relative to the user while seated at a table. Comprehensive tracking of complete arm orientation (including shoulder and elbow orientation) was not the focus of this study.

A. Variance Analysis

An analysis of accuracy levels for each gesture was completed. Accuracy levels for movements along the varied axes were consistently more accurate (Fig. 8) than movements along the forward axis (Fig. 7). Movements on varied axes have greater variance in orientation, allowing the model to discriminate movements more accurately.

Movements in the forward axis (Fig. 7) have more similar orientation readings, possibly making resulting differentiation more difficult. We notice high average accuracies and lower standard deviations for movements where the wrist is close to the body. As the wrist is more displaced from the body, average accuracies decrease slightly to 93%, and variance increases.

B. Inter-patient Performance

An analysis of accuracy levels across patients was also performed (Fig. 9). Accuracy was consistent across patients, with average accuracy of 98% and standard deviation of 1%.

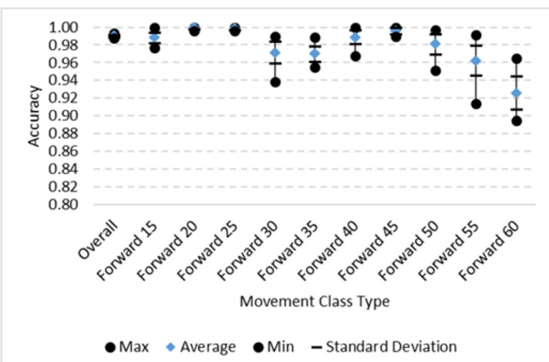

Fig. 7. Variance Analysis of forward movements.

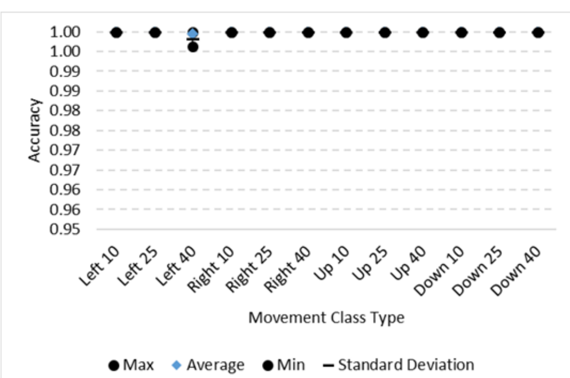

Fig. 8. Variance analysis of movements in multiple directions.

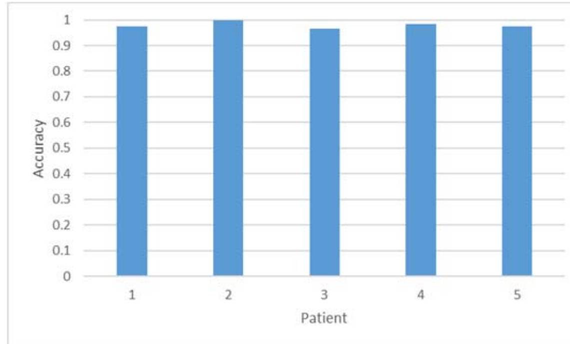

Fig. 9. Relative accuracy levels of 5 patients in this study.

V. Conclusion

In this paper, we have demonstrated a wearable device that uses infrared sensors to increase the motion sensing accuracy of conventional IMU sensor wearables. High average accuracies of 98% were realized across five participants, without requiring any normalization of results to varying body sizes of participants. These findings indicate a strong inter-patient similarity in arm movement patterns, and improve on our previous results by testing an increased number of movement classes in different directions. We conclude that this design could be applied into motion sensing applications across different individuals with high degrees of accuracy in a transfer learning application. In this application, exercise data from various patients can be combined to collectively improve the accuracy of the predictive machine learning model. This could allow realization of a device that is easily donned and calibrated to the movements an individual undergoing physical rehabilitation.

Future research will evaluate spatial accuracy limits of the device and incorporate a continuous tracking routine to allow spatial regression.

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