Synergistic Orthopaedic Fatigue Tracking Glove: SOFT Glove - Preview

Ben Allen[1], Martin S. Garrad[2], Carlos A. Cifuentes[1]

***Abstract*— Repetitive strain injury (RSI) is a major health issue with 200,000 new cases being reported per year within the UK alone, and common symptoms include cramping, prolonged pain, stiffness and weakness. This is especially prevalent within electrical assembly jobs, with a 40.2% chance that a worker suffers from some form of upper limb injury before retirement. A significant RSI cause is continuing to work after the onset of muscular fatigue. Existing solutions only focus on post-injury rehabilitation or support. Here, we introduce the SOFT glove which is able to detect fatigue through resistive bend sensors mounted to key locations on the hand, enabling workers to be notified of fatigue and potentially preventing the development of RSI. The viability of this design was validated in both a controlled study and a live sorting task. The trained classifier detected fatigue within both scenarios, with a minimum average accuracy of 95.67% when trained on only 15 seconds of data for controlled movements and 96.01% for 3 minutes of training data for a real-world task. Therefore, the SOFT glove can confidently predict the main RSI warning sign for repetitive work, potentially reducing RSI in the workplace.**

I. Introduction

Manual workers performing repetitive actions frequently suffer from long-term health conditions, such as carpal tunnel and RSI (Repetitive Strain Injury) with 200,000 cases reported in an average year in the UK [1]. These conditions lead to pain, cramping and stiffness of the hand if left untreated, severely reducing the quality of life [1]. The most common causes of RSI are over-exertion of the joints through repetitive motion and poor posture during work [2]. 24% of cases [3] are in manufacturing jobs, with electrical workers having a 40.2% chance of developing upper limb disorders [4]. These injuries lead to 2.6 million workdays lost in the UK per year, [1] culminating in a cost of £5-20 billion annually [5]. Early detection is key to avoiding injury and loss of work [2], but diagnosis requires a physical examination and X-ray [6]. Current devices only support post-injury patients, motivating the need for a real-time tracking device to highlight warning signs avoiding injury [7].

Working whilst over-exerted is a common cause of RSI [2], with the fatigue of the worker during the day being the most important warning signal [8]. Several systems for on-line fatigue detection have previously been presented in the literature: For example, some systems look at the force produced by the user's grip on a steering wheel or track facial movement [9] [10]. These methods are impractical for manual assembly as they require either fixed cameras which don't work within a moving environment or sustained grip force which doesn't allow for moving hand positions. Jerk analysis has been measured by optical fibres [11] enabling analysis of acceleration during movements, suggesting joint accelerations become less uniform as fatigue increases, likely due to the body reducing energy consumption through muscle prioritisation [12].

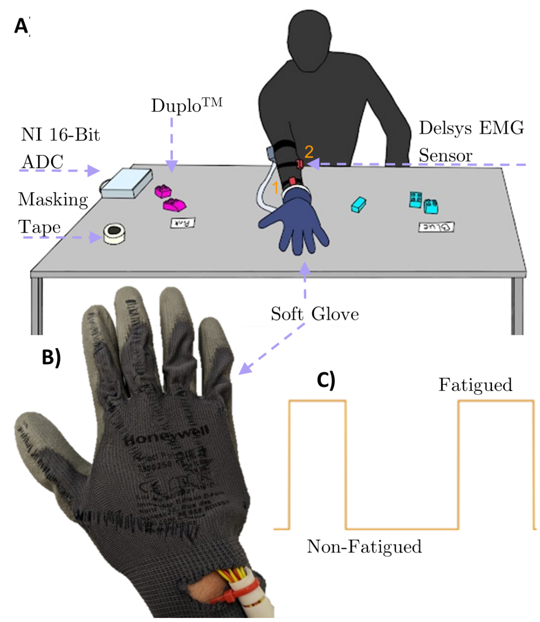

Fig. 1. The SOFT glove system. A) the experimental setup was used to test the viability of the glove by sorting coloured Duplo blocks into two categories. B) The SOFT glove consisting of 8 bend sensors sewn into a MaxiFex Glove, C) Results gathered from the glove for several fatigue cycles

Many commercial systems such as the Cyber Glove [13] exist to measure joint data. However, these systems contain an overabundance of sensing leading to large costs. One interesting approach to reducing the needed computation for real-time monitoring is to utilise postural hand synergies [14]. Here finger movements are combined into postural synergies based on the covariance of finger joints with the first two covering 84% of day-to-day movement [14]. Attempts have been made to utilise the synergies as control methods [15] [16] with some achieved via low-cost sensing techniques [17], but fatigue has not been measured in this way.

As fatigue monitoring has not been measured accurately

*This work was funded by the EPSRC Centre for Doctoral Training in Robotics and Autonomous Systems (FARSCOPE).

[1]Ben Allen and Carlos Cifuentes are with the Bristol Robotics Laboratory, University of the West of England, Bristol, UK. ben2.allen@live.uwe.ac.uk, carlos.cifuentes@uwe.ac.uk

[2]Martin S. Garrad is with the Bristol Robotics Laboratory, Engineering Mathematics and Technology, University of Bristol, UK. m.garrad@bristol.ac.uk

through hand positioning similar methods can be observed in gesture control, another more researched field. Optimisation of hand and gesture tracking techniques have been attempted [18] using postural synergies, allowing for accurate measurement and prediction but due to using optical markers on the hand a loss of reliability is noted if markers are misaligned on the user. Some gesture control systems use the forearm and wrist muscles [19], coupled joints within the fingers [20] or EMG/FMG systems detecting user movement through muscle intention [21]. Soft approaches [22] [23] [24] exist to detect hand gestures but require more complex manufacturing techniques and designs which are not robust enough for the manufacturing sector. Hybrid systems exist to battle this [25] producing results capable of accurately detecting hand motion up to a 97% hit rate, but require static gestures to do so making them unsuited for a constantly moving environment.

Overall fatigue is difficult to track as it cannot be directly measured through a single quantitative scale such as temperature, and current systems often struggle to predict fatigue within a moving environment. This is due to systems either relying on cameras or fixed hand positions which do not function with a moving user completing dexterous tasks. EMG systems [26] [27], which are the most common detection approach, can keep up with a moving environment but suffer greatly from long setup times, misalignment errors and accuracy reduction due to hair or skin colour [28] making them ill-suited for a working environment where time is money [29].

Here we introduce the SOFT glove which combines bend-sensing and a random forest classifier to detect fatigue. This approach allows for a less intrusive device compared to EMG which is usually mounted onto the forearm and wrist, with the SOFT glove being about as restrictive as a normal MaxiFlex glove, but able to detect fatigue quickly and accurately both in a controlled environment and a real-world repetitive task, without the user being confined to a zone.

The key contributions of this research are:

- The introduction of the SOFT glove concept and its ability to detect joint movement and fatigue.
- Evaluation of the SOFT gloves' ability to detect fatigue in both a controlled and real-world environment, showing performance comparable to the gold standard of EMG fatigue detection.

The following section will discuss the fabrication and working principles of the SOFT glove, with sections III and IV introducing the idealised and real-world fatigue detection tasks. Section V will discuss the overall system with the paper being concluded in section VI.

II. Working Principle of the SOFT Glove

A. Glove Fabrication

Joint positions are collected through 8 resistive flex sensors (Spectra symbol FS, PiHut UK, 55mm length), at a rate of 100Hz, placed over the MCP (Metacarpal) joint and

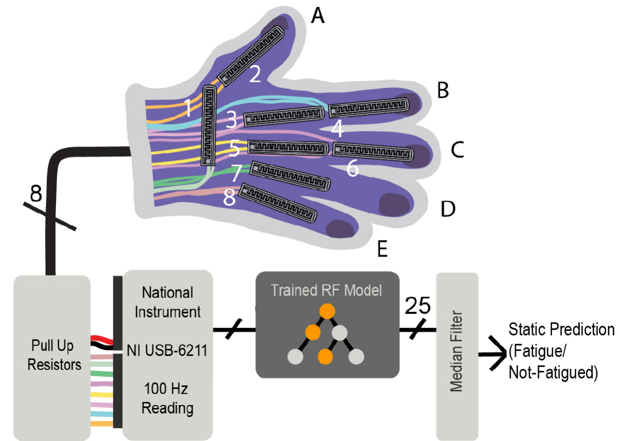

Fig. 2. Working principle of the SOFT glove showing the 8 sensor locations mounted across the fingers A-E. A pull-up resistor circuit and data collection box gather the 8 Sensor readings. The data goes into the classifier to determine if the user is fatigued. A median Filter is applied across every 25 samples to reduce error

the DIP (Distal Inter-Phalangeal) and PIP (Proximal Inter-Phalangeal) joints within the hand as shown in figure 2. The locations were chosen to cover all finger joints, with initial experimentation showing only the MCP joints of the pinky and ring finger added accuracy to the system. The sensors are sewn onto the inside of an ATG-Maxiflex glove at the selected locations with the uncovered side of the sensor facing towards the glove. These positions allow for the measurement of hand movement with a finer detail focusing on fingers A-C which are preferred for precision work. The flex sensor data is fed through a potential divider to a 16-bit data acquisition box (National Instruments, NI-USB-6211).

B. System and Classifier Design

To determine whether a user is suffering from fatigue, data is collected pre/post an isometric exercise known to cause fatigue [30]. The recorded data from the glove is used to train a random forest classifier, selected over others because of its high generalization accuracy for high dimensional data (1 x 8 data array collected 100 times a second) and fast training phase time [31] [32]. Testing data is fed through the random forest using readings from all 8 sensors to ascertain a prediction, and then through a rolling median filter of 25 values to smooth the output and reduce the impact of abnormal results. Raw position readings are used as this was the quickest approach to test the fatigue-predicting capabilities. Velocity, acceleration or jerk were not input as a variable into the system. Due to the high accuracy predictions observed from the raw readings, the extra calculation time was deemed unnecessary for this initial proof of concept.

A median filter of 5 (98.97%), 15 (99.55%), 25 (99.75%) and 50 (99.957%) were tested giving the corresponding relative accuracies for the controlled task. Therefore the sampling was set to 25 readings as it allowed for a significant smoothing of noise, without reducing the fidelity of the results or delaying the prediction of fatigue severely, as past that point very little accuracy improvement was noted.

Fig. 3. Table depicting the various hand poses seen within the experiment with synergies 1 & 2 the desired movements for the idealised experiment

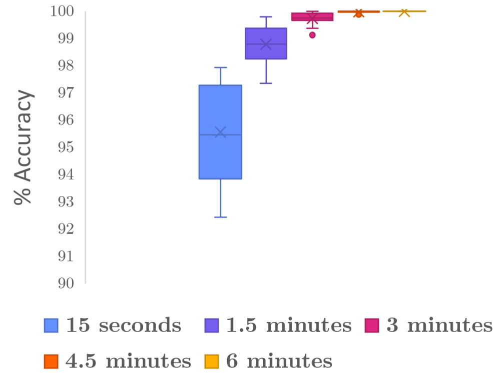

Fig. 4. A box and whisker plot showing the accuracies for the 5 models each trained on a reducing amount of data when tested on the full dataset

Training data was collected within an idealised environment and a real-world task. Various models were trained to determine the minimum calibration time needed for classification. This is a priority; the lower the training time, the less work is lost due to setup. To further reduce this, synergistic movements as shown in figure 3 a-f are used to group joints based on co-variances. This allows for the calibration movements to represent around 85% of everyday motions reducing the movement set to 2 grips whilst still having a high chance of predicting the fatigue.

III. Fatigue Detection Viability Study

A. Data Aquisition

Initial viability was tested by repeating 2 controlled movements called Synergy 1 (figure 3a-c) and Synergy 2 (figure 3d-f). The data was collected at a rate of 100Hz with the following method.

The user was told which synergy to start with and asked to switch between the maximum and minimum positions every 1.5 seconds. The movement set was repeated for 1 minute or 40 cycles before swapping to the other synergy and cycling at the same rate. Both cycles are repeated a further time to gain 2-minute-long cycles of each synergy. A small rest of 10s was given between each synergy change so the user would not become fatigued prematurely. A 40BPM metronome was used to keep timing with users being advised to start the movement transition on the click and aim to complete it just before the next click to have continuous movement.

To introduce fatigue into the hand an isometric exercise was used where the movement was restrained using a roll of masking tape (as shown in figure 3.h), and the user was asked to push their fingers out equally so that they could lift the masking tape without it falling, holding the muscle pulse for two minutes [30] or until fatigue was self-reported or observed. The above procedure of synergy cycling was repeated with the fatigued hand for only 30 seconds per sample, giving a total of 2 minutes of data comprising 2 sets of each synergy movement.

Data was collected from 20 participants aged 19-62 (average age 27.71, split 7:13 male to female). Data was collected following the ethical practices of The University of Bristol and The University of the West of England.

B. Results

Four models were trained using 6 minutes, 4.5 minutes, 3 minutes, 1.5 minutes and 15 seconds of training data per participant respectively. The models were then fed the complete controlled data set and their prediction accuracy can be seen in figure 4 demonstrating the average and per-participant accuracy.

Figure 4 shows the 6-minute and 4.5-minute models have little deviation, with this stepping up slightly for the 3 and 1.5-minute models with all accuracies being above 98%. The 15-second data shows the largest deviation with an average accuracy of around 95.57%. To minimise training time a value of 3 minutes of training data per participant was chosen for the subsequent tests.

C. Discussion

These results show that the SOFT glove can predict fatigue within a controlled environment with up to 100% accuracy when using 80% of the data to train. This is a large section of the dataset, but for only 15 seconds of data, an accuracy of 95.57% can still be observed allowing for a minimal initial calibration time per user decreasing lost work time.

The median filter introduced into the processing pipeline has a large effect on the accuracy raising it by an average of 8.17% per model. The downside is that it reduces the prediction rate to once every 5 seconds instead of 5 times a second. However, RSI is due to prolonged working whilst fatigued where an accurate prediction happening at a frequency greater than once a minute is sufficient. This accuracy could be further increased through a threshold filter forcing values to be fatigued or non-fatigued, but this results in a loss of analogue or intermediate states where fatigue may have started to occur but be lower than the threshold.

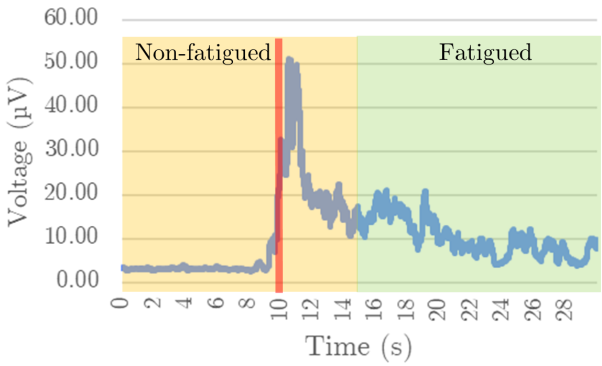

Fig. 5. An extract of EMG data showing the onset of the isometric exercise marked with a red line and the reduction in amplitude demonstrating fatigue following the exercise

Compared to previous studies looking at fatigue prediction from either bend sensing [33], or IMU jerk sensing [11] an improvement can be seen in repeatability and noise reduction. More developed systems such as driver fatigue detection [10] showed detection rates of 86.6% for 36 participants. The SOFT glove system can detect fatigue with a much higher accuracy of 95.57% requiring only 15 seconds to train.

IV. Detection of Fatigue within a Repetitive Sorting Activity

A. Data Acquisition

We now show that fatigue detection can be repeated in a real-world scenario. Participants were asked to sort Duplo™ blocks one at a time into either pink or blue areas, marked on the table in front of them to mimic a repetitive assembly task. The participants could only use their gloved hand and had to sort the blocks one by one preferably slowly. The experiment consisted of an initial 3-minute non-fatigued sorting session, before introducing fatigue into the hand using the same isometric process as described in section III.A for two minutes. The sorting task was continued for a further 2 minutes to collect the fatigued data set for each user.

During this experiment, 2 Delsys Trigno EMG sensors were placed on the user's forearm over the palmaris longus (1) and extensor digitorum (2) as seen in figure 1, sampling at 100 readings a second for the completion of the experiment (7 minutes). This was used to validate that fatigue had occurred via an amplitude drop in the MVP (Maximum Voluntary Pulse) of the EMG readings [34].

B. Results

Predictor	T-Positive	F-Positive	T-Negative	F-Negative
Controlled	0.9993	0.0007	0.9930	0.0070
Real World	0.9595	0.0405	0.9207	0.0793

TABLE I

Fatigue was predicted using a Random Forest model trained on the controlled and non-controlled task data. Figure 6 shows the prediction accuracy per participant with the average value of 96.01%.

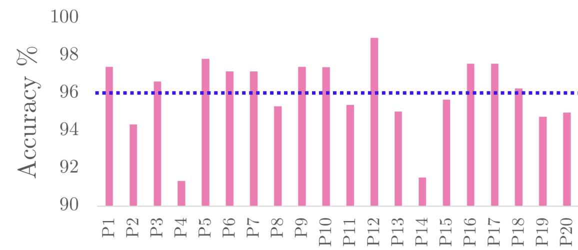

Fig. 6. A histogram showing the accuracies per participant for prediction during the sorting task.

C. Discussion

This study shows fatigue can be predicted for all users with an average accuracy of 96.01%. A slight reduction in true positive and negative rates can be noted in Table I compared to the controlled dataset. There is a reduction of accuracy for participants 14, and 4 but on examination of the EMG data, a lower change in amplitude can be seen post-exercise suggesting lower fatigue levels. This variation could be due to the participant's fitness level causing a lower fatigued state post-exercise. The effect of physical fitness on EMG fatigue reliability has been well noted [33]. Furthermore, the recovery time of 6 minutes after the idealised experiment may not have been sufficient for some users.

For surface electrode EMG fatigue systems, the best accuracies measured on healthy patients are 95.18% on the lower limbs, [35] and 94.09% on bicep brachii [36] which is comparable to the 96.01% from the SOFT glove. The increase in accuracy could be due to the SOFT glove using high-level movements for its predictions giving 8 input variables, whereas the EMG systems use low-level muscle impulses with 4 inputs into the system. Additionally, the SOFT glove system is based on binary classification which helps to improve accuracy and uses repetitive non-anaerobic movements compared to the sustained periods of exercise used across the EMG studies [35] [36] making it more suited to an assembly. Furthermore, the improvement in accuracy is only within the specific tasks undertaken during the studies. Surface EMG-based systems are more easily generalised to other tasks as they depend on muscle maximum contraction so are agnostic of the task the hand is completing. This is less important for manual assembly tasks though as they consist of repeated actions that can be predicted.

V. Demonstration of Continuous Fatigue Monitoring

Finally, we demonstrate that the SOFT glove can detect multiple switches between fatigued states by having a single user repeatedly form a fist grip whilst under various states of fatigue. EMG readings were collected with Delsys Sensors following the positions shown in figure 1 to give the baseline. The fatigue states were achieved using the isometric exercise in figure 3.h. and a period of rest without recording to return to a normal state. Figure 7 shows that the trained model was able to predict fatigue with 98.79% accuracy with the EMG data showing MVP amplitude drops at the fatigued state

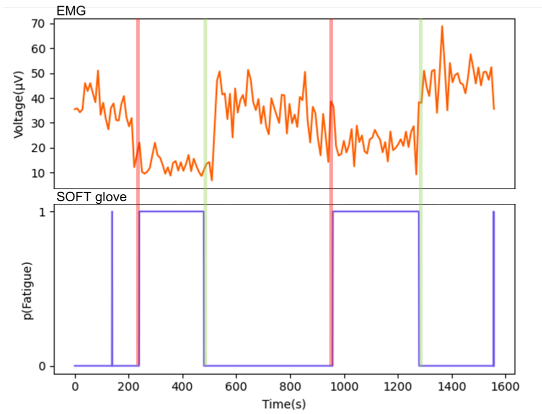

Fig. 7. A Graph showing the predictions for a continuous fatigue study with periods of isometric exercise marked with red lines followed by rest periods marked in green, with the corresponding EMG data above

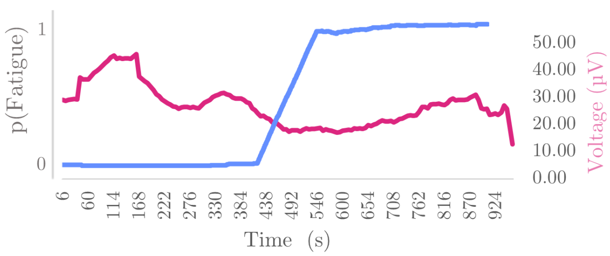

Fig. 8. A Graph showing the mean predictions(blue) and EMG data (pink) for a continuous run study where no exercise was performed and fatigue was entered through continuous repetition of movement

lining up with the labelled data. A further study was done where a single participant repeated the synergy 1 movement (figure 3 a-c) for a total of 16 minutes. Fatigue was self-reported at around 546 seconds with the EMG validating that muscular fatigue happened at 530 seconds by a drop in the MVP amplitude. Figure 8 shows initial fatigue forming at around 520 seconds with a more definite change at 600 seconds. This shows that the system will start to detect fatigue as it occurs but it takes some time for fatigue to fully set in giving a clearer more determined signal. Initially, once fatigue has occurred and the MVP is no longer being reached the RMS signal will start to rise again as the user switches to submaximal voluntary contractions [37]. This is shown in the slow rise of amplitude after initial fatigue is noted.

VI. Discussion of SOFT Glove Concept Evaluation

In this work, we have shown that SOFT glove can achieve fatigue prediction within an idealistic (99.74%) and a real-world picking task (96.01%). Similar joint movement-based fatigue detection systems [38] [33] did not get coherent results across all participants, due to differences in body types and activity levels of participants. These results make the SOFT glove the first wearable soft device that can repeatedly and accurately detect fatigue within the hand. Comparing the SOFT glove to known EMG-based systems [26] [27] it

Classifier	Sensitivity	Specificity	Accuracy
SOTF-Glove Control	98.59	99.97	99.74
SOFT-Glove Non Control	87.38	97.55	96.01
EMG Random Forest [39]	85.74	91.66	88.7
EMG SVM-polynomial [39]	90.38	88.54	89.46
Shimmer 3 IMU [40]	1	0.79	N/A

TABLE II

A Table comparing the effectiveness of 5 different algorithms in prediction of fatigue by observing a user

can be seen that the gathered amplitude signals from the Delsys sensors match the force profiles and fatigue curves in the literature. This shows that the isometric exercise used achieves a fatigued state and the glove's response follows the drop in EMG of the participants. As the SOFT glove relies on finger movement, problems common with EMG such as misalignment, hair on the skin, the complexion of the skin, and residue or oils on the skin, were not observed. The effects of hair, complexion and misalignment were noted during the user study for the EMG, with re-adjustments of EMG sensors having to be made to get a reliable signal.

The SOFT glove was less than ideal for users with smaller hand sizes, and issues with the glove being baggy for users with more slender hands meant there was a significant amount of movement inside the glove before it started following the user's motion. However, fatigue was still predicted for every user likely because the random forest algorithm can identify differences in the movement patterns of the user, so it is irrelevant which sensor detects it. The addition of the bend sensors led to a stiffness increase measured at 2.4/m In the future this could be reduced through the use of soft bend sensors [20]. Table II shows an analysis of the random forest predictions for both the controlled and non-controlled experiments, compared to a shimmer 3 IMU-based fatigue detector [40] and two EMG GA-based feature selection predictors [39]. This data shows that the SOFT glove can detect fatigue with higher accuracy than the other methods, however, the specificity is rather high suggesting that the model may be overfitting. The control scenario shows a slightly more overfit model mainly resulting from it being a set of controlled movements rather than allowing the user to choose grasps. This overfitting problem may be less of an issue if the user is repeating the same actions.

The limitations of the paper mainly focus on the reduced amount of data collected. Although a sufficient sample size was used to defend the initial hypothesis and prove viability there is still room for development. Noted issues to do with over-fitment could be addressed through increased data collection including multiple object sets and tasks with a larger pool of users. Theoretically, with a big enough dataset, the glove may not need any calibration functioning using online training to fine-tune the model to the user.

VII. Conclusion

The SOFT glove can predict fatigue in an idealised environment with an accuracy of 99.74% and in a real-world environment with 96.01%. This prediction method is comparable to what is seen from RMS EMG-based fatigue systems but is minimally affected by misalignment errors and body conditions, with a lower setup time. This fatigue detection forms the pivotal first step in the real-time detection of RSI warning signs and with further development could support repetitive assembly workers within their respective fields. Therefore the SOFT glove can be considered the first device to detect fatigue in real time using bend sensing with accuracy comparable to EMG-based systems.

References

[1] "RSI in the Workplace inc Work Related Upper Limb Disorder and Computing | AbilityNet."

[2] "Repetive strain injury: Nhs health," May 2022.

[3] S. E. Luckhaupt, J. M. Dahlhamer, B. W. Ward, M. H. Sweeney, J. P. Sestito, and G. M. Calvert, "Prevalence and Work-Relatedness of Carpal Tunnel Syndrome in the Working Population, United States, 2010 National Health Interview Survey," *American journal of industrial medicine*, vol. 56, pp. 615–624, June 2013.

[4] K. T. Palmer, E. C. Harris, and D. Coggon, "Carpal tunnel syndrome and its relation to occupation: a systematic literature review," *Occupational Medicine*, vol. 57, pp. 57–66, Jan. 2007.

[5] RSI-Awareness, "Rsi facts and figures."

[6] N. I. of Neurological Disorders and Stroke, "Carpal Tunnel Syndrome."

[7] N. Gautam and A. Shrivastava, "A Review on Risk Factors and Diagnosis of Carpal Tunnel Syndrome," *ECS Transactions*, vol. 107, pp. 6921–6932, Apr. 2022.

[8] D. A. Mandal, "Causes of repetitive strain injury (rsi)," May 2023.

[9] F. Baronti, F. Lenzi, R. Roncella, and R. Saletti, "Distributed sensor for steering wheel grip force measurement in driver fatigue detection," in *Automation & Test in Europe Conference & Exhibition 2009 Design*, pp. 894–897, Apr. 2009. ISSN: 1558-1101.

[10] R. Li, Y. V. Chen, and L. Zhang, "A method for fatigue detection based on Driver's steering wheel grip," *International Journal of Industrial Ergonomics*, vol. 82, p. 103083, Mar. 2021.

[11] L. Zhang, M. M. Diraneyya, J. Ryu, C. T. Haas, and E. Abdel-Rahman, "Assessment of Jerk As a Method of Physical Fatigue Detection," American Society of Mechanical Engineers Digital Collection, Nov. 2018.

[12] J. C. Cowley, J. B. Dingwell, and D. H. Gates, "Effects of local and widespread muscle fatigue on movement timing," Dec 2014.

[13] "CyberGlove Systems LLC."

[14] M. Santello, M. Flanders, and J. F. Soechting, "Postural hand synergies for tool use," *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, vol. 18, pp. 10105–10115, Dec. 1998.

[15] F. Ficuciello, "Synergy-Based Control of Underactuated Anthropomorphic Hands," *IEEE Transactions on Industrial Informatics*, vol. 15, pp. 1144–1152, Feb. 2019. Conference Name: IEEE Transactions on Industrial Informatics.

[16] N. J. Jarque-Bou, J. L. Sancho-Bru, and M. Vergara, "Synergy-Based Sensor Reduction for Recording the Whole Hand Kinematics," *Sensors*, vol. 21, p. 1049, Jan. 2021. Number: 4 Publisher: Multidisciplinary Digital Publishing Institute.

[17] M. Bhuyan, A. K. Talukdar, P. Gupta, and R. H. Laskar, "Low Cost Data Glove for Hand Gesture Recognition by Finger Bend Measurement," in *2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, pp. 25–31, Aug. 2020.

[18] "Synergy-based hand pose sensing: Reconstruction enhancement."

[19] E. Fujiwara and C. K. Suzuki, "Optical Fiber Force Myography Sensor for Identification of Hand Postures," *Journal of Sensors*, vol. 2018, p. e8940373, Mar. 2018. Publisher: Hindawi.

[20] S. Shin, H. U. Yoon, and B. Yoo, "Hand Gesture Recognition Using EGaIn-Silicone Soft Sensors," *Sensors*, vol. 21, p. 3204, Jan. 2021. Number: 9 Publisher: Multidisciplinary Digital Publishing Institute.

[21] S.-W. Byun and S.-P. Lee, "Implementation of Hand Gesture Recognition Device Applicable to Smart Watch Based on Flexible Epidermal Tactile Sensor Array," *Micromachines*, vol. 10, p. 692, Oct. 2019. Number: 10 Publisher: Multidisciplinary Digital Publishing Institute.

[22] J.-B. Chossat, Y. Tao, V. Duchaine, and Y.-L. Park, "Wearable soft artificial skin for hand motion detection with embedded microfluidic strain sensing," in *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2568–2573, May 2015. ISSN: 1050-4729.

[23] G. Gu, H. Xu, S. Peng, L. Li, S. Chen, T. Lu, and X. Guo, "Integrated Soft Ionotronic Skin with Stretchable and Transparent Hydrogel–Elastomer Ionic Sensors for Hand-Motion Monitoring," *Soft Robotics*, vol. 6, pp. 368–376, June 2019. Publisher: Mary Ann Liebert, Inc., publishers.

[24] J.-W. Lin, C. Wang, Y. Y. Huang, K.-T. Chou, H.-Y. Chen, W.-L. Tseng, and M. Y. Chen, "BackHand: Sensing Hand Gestures via Back of the Hand," in *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology*, UIST '15, (New York, NY, USA), pp. 557–564, Association for Computing Machinery, Nov. 2015.

[25] W.-C. Chuang, W.-J. Hwang, T.-M. Tai, D.-R. Huang, and Y.-J. Jhang, "Continuous finger gesture recognition based on flex sensors," Sep 2019.

[26] J. Wang, M. Pang, P. Yu, B. Tang, K. Xiang, and Z. Ju, "Effect of Muscle Fatigue on Surface Electromyography-Based Hand Grasp Force Estimation," *Applied Bionics and Biomechanics*, vol. 2021, 2021. Publisher: Hindawi Limited.

[27] J. Sun, G. Liu, Y. Sun, K. Lin, Z. Zhou, and J. Cai, "Application of Surface Electromyography in Exercise Fatigue: A Review," *Frontiers in Systems Neuroscience*, vol. 16, 2022.

[28] A. Yound, L. Hargrove, and T. Kuiken, "The Effects of Electrode Size and Orientation on the Sensitivity of Myoelectric Pattern Recognition Systems to Electrode Shift."

[29] TMSi, "Tips for getting good emg signals," May 2023.

[30] V. Soto-Leon, C. Alonso-Bonilla, D. Peinado-Palomino, M. Torres-Pareja, N. Mendoza-Laiz, L. Mordillo-Mateos, A. Onate-Figuerez, P. Arias, J. Aguilar, and A. Oliviero, "Effects of fatigue induced by repetitive movements and isometric tasks on reaction time," *Human Movement Science*, vol. 73, p. 102679, 2020.

[31] O. Mbaabu, "Introduction to random forest in machine learning," Dec 2020.

[32] S. Wen, T. M. Kurc, L. Hou, J. H. Saltz, R. R. Gupta, R. Batiste, T. Zhao, V. Nguyen, D. Samaras, and W. Zhu, "Comparison of Different Classifiers with Active Learning to Support Quality Control in Nucleus Segmentation in Pathology Images," *AMIA Summits on Translational Science Proceedings*, vol. 2018, pp. 227–236, May 2018.

[33] H. B. Skinner, M. P. Wyatt, J. A. Hodgdon, D. W. Conard, and R. L. Barrack, "Effect of fatigue on joint position sense of the knee," *Journal of Orthopaedic Research*, vol. 4, no. 1, pp. 112–118, 1986. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jor.1100040115.

[34] H. A. Yousif, A. Zakaria, N. A. Rahim, A. F. B. Salleh, M. Mahmood, K. A. Alfarhan, L. M. Kamarudin, S. M. Mamduh, A. M. Hasan, and M. K. Hussain, "Assessment of muscles fatigue based on surface emg signals using machine learning and statistical approaches: A review," in *IOP conference series: materials science and engineering*, vol. 705, p. 012010, IOP Publishing, 2019.

[35] J. Wang, S. Sun, and Y. Sun, "A muscle fatigue classification model based on lstm and improved wavelet packet threshold," *Sensors*, vol. 21, no. 19, p. 6369, 2021.

[36] K. DB *et al.*, "Automated detection of muscle fatigue conditions from cyclostationary based geometric features of surface electromyography signals.," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 25, no. 3, pp. 320–332, 2021.

[37] F. N. Jamaluddin, F. Ibrahim, and S. A. Ahmad, "A New Approach to Noninvasive-Prolonged Fatigue Identification Based on Surface EMG Time-Frequency and Wavelet Features," *Journal of Healthcare Engineering*, vol. 2023, p. e1951165, Jan. 2023. Publisher: Hindawi.

[38] C. Ranniger, D. Akin, C. Henshaw, S. Sell, and E. Sorenson, "Joint angle and muscle fatigue detection in the hand during EVA simulation operations," in *Space Programs and Technologies Conference*, American Institute of Aeronautics and Astronautics. _eprint: https://arc.aiaa.org/doi/pdf/10.2514/6.1996-4222.

[39] P. A. Karthick, D. M. Ghosh, and S. Ramakrishnan, "Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms," *Computer Methods and Programs in Biomedicine*, vol. 154, pp. 45–56, Feb. 2018.

[40] Z. Sedighi Maman, M. A. Alamdar Yazdi, L. A. Cavuoto, and F. M. Megahed, "A data-driven approach to modeling physical fatigue in the workplace using wearable sensors," *Applied Ergonomics*, vol. 65, pp. 515–529, Nov. 2017.