Development of a Plantar Pressure Postural Analysis & Biofeedback System For WMSD Corrective Therapy

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Impact of WMSDs

Work-related musculoskeletal disorders (WMSDs) account 130 million total health care encounters annually (CDC) – with an annual economic cost of WMSDs to between \$45 and \$54 billion. In addition to the remarkable financial burden these injuries inflict upon industry and the healthcare system, WMSDs affect workers' physical and mental health for the duration of their lives.

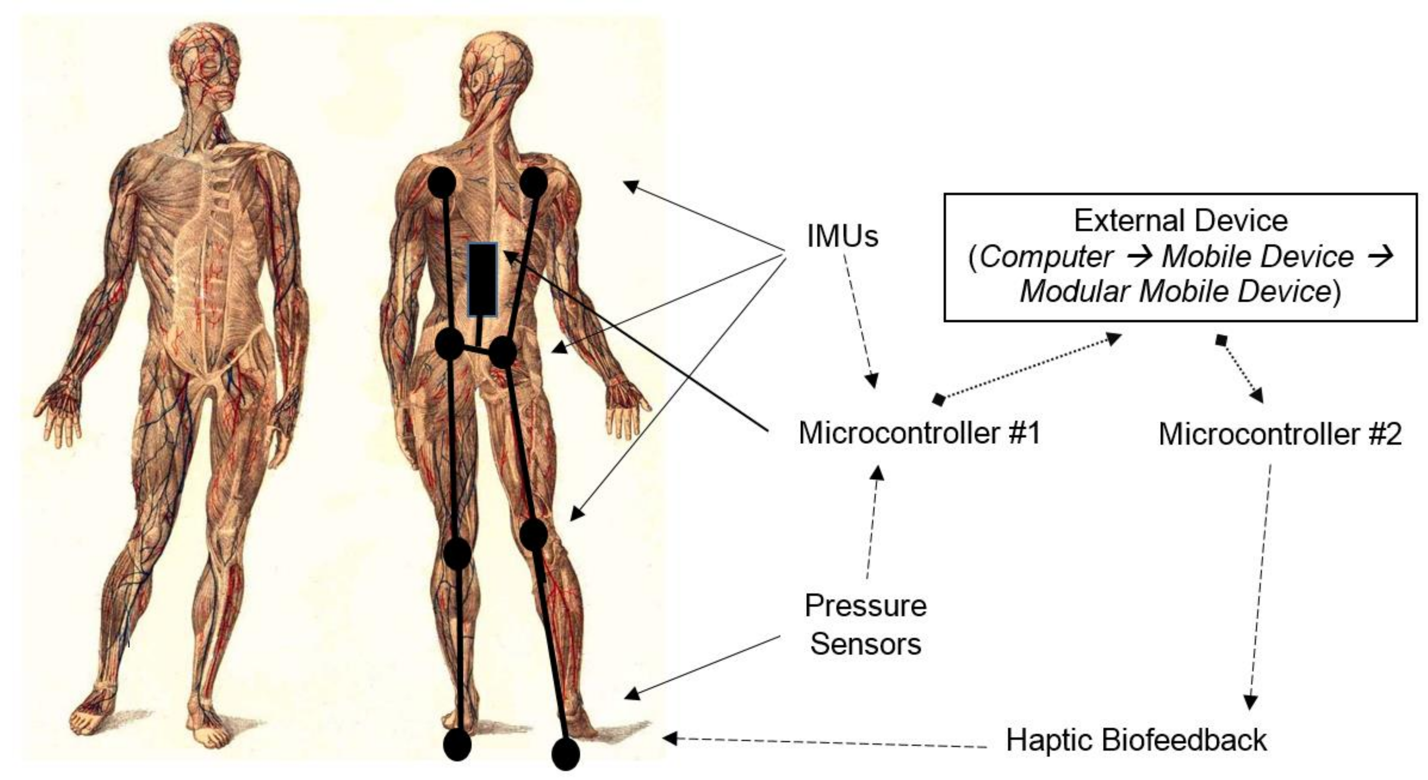
WMSD Detection Tools

- Ergonomics Methods
  - Rapid Entire Body Assessment (REBA)
  - Rapid Upper Limb Assessment (RULA)
  - NIOSH Lifting Equation
  - Hazard Analysis Tool (Snook Tables)
- Medical Methods
  - Medical History & Physical Examination
  - Electromyography (EMG)
  - Imagery (e.g., X-Ray, CT, MRI, Ultrasound)
- Pedobarography
- Motion Capture

Few options for accurate, portable, and affordable WMSD detection and therapy exist. The closest commercial application – Lumo Lift – provides only upper-body posture data. For full-body WMSD detection, analysis, and therapy – a new device must be designed.

Method

Consequently, our team is developing a bioinstrumentation system that consists of pressure (piezoelectric) sensors attached to the bottom sole (plantar region) of the feet, and inertial measurement unit (IMU) sensors at the shoulders, hips, and knees; all connected to an Arduino microcontroller that algorithmically calculates the individual's deviation from healthy standing posture and provide biofeedback via haptic vibrations in offending areas of the body – to assist as a corrective behavioral treatment in prevention or therapy for work-related musculoskeletal disorders (WMSDs) relating to posture.



Our team first developed anthropometric mannequin models in CATIA in order to determine load forces and moments of the human body at work and rest. Single joint biomechanical analyses were conducted to determine both proximal and distal forces and moments for the legs, feet, thighs, arms, forearms, neck, and trunk of the human body in flexion, extension, pronation, supination, abduction, adduction, elevation, depression, and rotation as applicable. Data concerning joint sheer and compression loads involving forward acceleration, as well as horizontal, vertical, and lateral forces were also calculated.

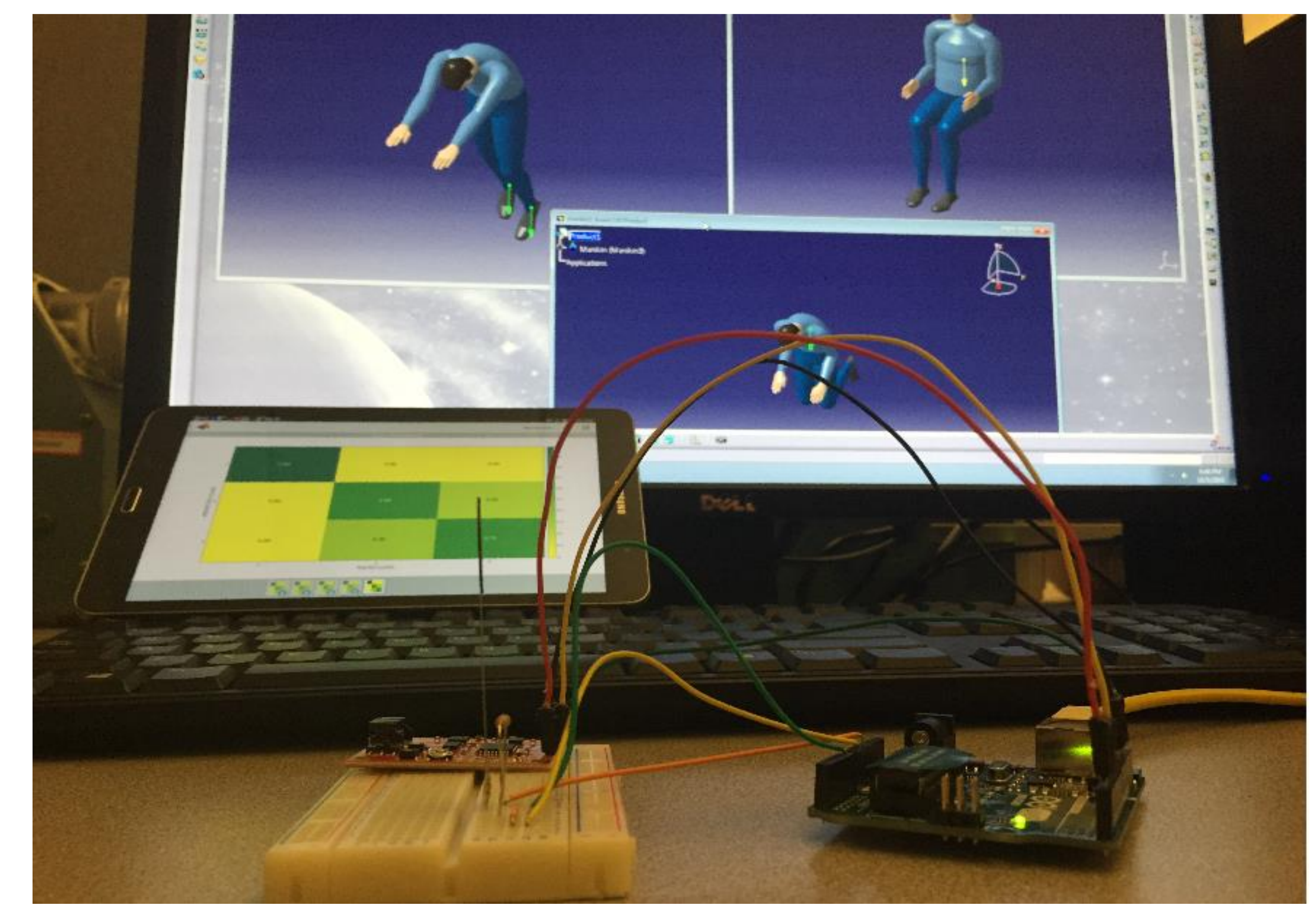
The data derived from these models were inputs for a Multivariate Gaussian Analysis serving as the machine learning technique. This model was trained to calculate postural deviation values based on iterations of the simulation data. The primary output of this machine vision included a confusion matrix of predicted and tested class states, signifying the accuracy by which the algorithm is able to detect ideal and deviant posture and plantar pressure for both at work and rest. An application for mobile devices (Android) was then developed to display the certainty matrix as a precursor for future biofeedback and mobile development.

Results

Our results demonstrate the viability of this device as well as the method of in vivo data collection. The algorithm was likewise successful, in that accuracy for detection of states / classes as identified in the certainty matrix range between .70 and 1.00 accuracy in pilot tests dependent on the complexity of the mannequin movement and position.

Discussion

Our initial development of the reference model, posture deviance detection algorithm, machine learning process, and mobile application prove the feasibility of this device. However, significant improvements to our system are needed in preparation for the first device prototype.



Foremost, our analyses signify a lack of sensitivity and a high margin for error in the current commercial inertial measurement units (IMUs) and plantar pressure sensors used for this device. Upgrades are required. Second, neural network analyses will replace the MGA used for the rapid prototype current machine learning process. Next, user data will be integrated into the models as a wider range of motions and body positions are understood by the system and addressed by the posture deviance detection algorithm. Incorporation of the non-intrusive haptic biofeedback will follow. Lastly, app data will be customized to the needs of users following a series of usability tests using human factors and ergonomics methods to be conducted throughout the iterative product design process.

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