A Motion Capture System for Hand Movement Recognition

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Abstract. One of the most frequently-used body regions in daily activities is the upper limbs, and many of the work-related musculoskeletal disorders occur in this area, mainly the hands. We highlight the importance of studying hand movements executed at work, and how they affect workers' health and productivity. Data were collected from a hand-motion capture system conformed by six inertial measurement units and six resistive force sensors from hand and fingers movements. Two common hand movements were analyzed using wrist flexion-extension with a small ($-15°$ to $15°$) and medium ($<-15°$ and $>15°$) range of motion and flexion-extension movement with the hand pronated-supinated. Data were classified by traditional methods. A more complex movement involving a 3-finger spherical grip was also recorded. It was found that the lectures from the six inertial sensors and the six force resistive sensors showed a pattern that facilitates the recognition of basic and more complex movements (flexion-extension and spheric handgrip) through visual analysis of the plotted data, even at different ranges of motion.

Keywords: Wrist flexion-extension · Wrist pronation-supination · Spherical grip · Inertial measurement units · Resistive force sensors

1 Introduction

One of the human body regions that is frequently used in daily and work activities are the upper limbs, mainly the hands [1]. Most manual-work at factories is highly repetitive and requires huge force and awkward postures to be executed, sometimes exceeding the workers' capacities [2]. This behavior can be the cause of many work-related musculoskeletal disorders, which represent a third of the injuries at work, a quarter of lost time, and one-fifth of permanent disabilities [3]. As a result, it is important to study the hand movements executed at work to see how they can affect workers' health and productivity.

Human Activity Recognition (HAR) has been widely used to analyze human–machine interactions [4, 5]. The main goal of RAH is to identify activities based on

N. L. Black et al. (Eds.): IEA 2021, LNNS 223, pp. 114–121, 2022.
https://doi.org/10.1007/978-3-030-74614-8_13

the information obtained through a sensory network, which has been possible by the development of low-cost, small-size, and high-computational-capacity technologies [6].

When handling the object, the subject can independently decide how to grasp it, increasing the complexity of the activity recognition [7]. Xue et al. [7] recommended that motion capture systems used in object handling recognition should include tactile and force sensors in addition to inertial sensors.

This study relies on the analysis of data collected by a hand-motion capture system conformed by inertial and force resistive sensors to determine its use in the classification of the hand and fingers movements.

2 Method

2.1 Motion Capture System and Data Collection

A data glove motion-capture system (MoCap) adapted from six inertial sensors with 9 degrees of freedom located on the proximal phalanges and the dorsal side of the hand, and six force resistive sensors, collocated on each fingertip and palm, were used to generate data regarding hand and fingers movements.

Data collected included ten variables for each finger and hand: triaxial acceleration (m/s^2), triaxial angular velocity (rad/s), triaxial magnetic field (μT), and the force exerted by each fingertip described by the voltage (V) measured by the master–slave system. Data processing used Matlab 2019b software in a laptop running Windows 10. The lectures from the inertial sensors were calibrated using *zero motion* and *zero rate* methods before data collection [8].

A simple validity procedure for the inertial and force resistive sensors was performed prior the measurements to assure the correct MoCap system-computer communication.

2.2 Experimental Design

Two movements using the dominant hand were performed to analyze the capability of the data glove in the recognition of the hand and fingers movement: wrist flexion-extension and spheric hand grip. The flexion-extension movement was based on the Rapid Upper Limb Assessment (RULA) criteria [9]. Movements within the range $-15°$ to $15°$ and movements in a wider range ($<-15°$ and $>15°$) were performed (Fig. 1a). A goniometer with $1°$ resolution was placed on the dorsal side of the hand to assure the movement was in the correct range.

Additionally, flexion-extension movement was recorded when the wrist was pronated, supinated, and in a neutral position (Fig. 1b). Both datasets were classified using the Classification Learner application from Matlab 2019b. Data were segmented based on a sliding window with size = 30 observations and step = 10 observations. Accuracy of k-nearest neighbors (k-NN), the support-vector machine (SVM), decision trees, and Naïve–Bayes algorithms were obtained as performance metrics [10].

The spheric hand grip was performed using five fingers. A compressible ball was used to reproduce the movement.

The results obtained for the two experimental movements were plotted and graphically analyzed to determine if it was possible to identify a movement pattern that could be used in classification methods.

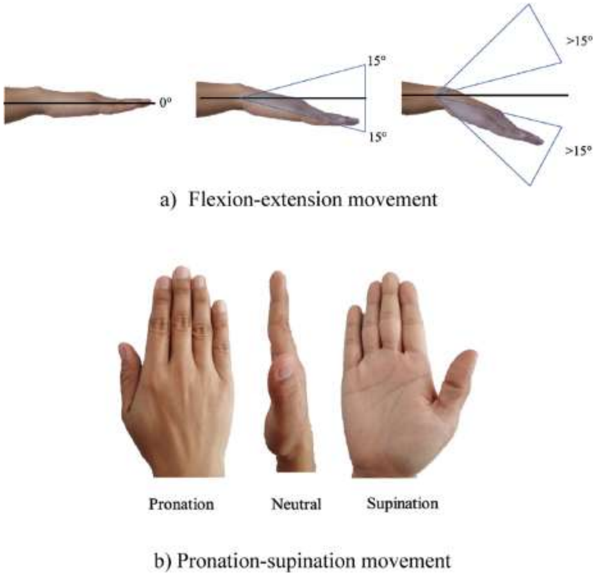


Fig. 1. Hand movements

3 Results

Data collected from the Mocap system while performing the wrist flexion-extension in the $-15°$ to $15°$ range of movement are presented in Fig. 2a, while the data collected from a wider range are presented in Fig. 2b. Only the readings obtained by the inertial sensor located on the dorsal side of the hand are presented because the fingers are not involved in the flexion-extension wrist movement considered in this study. The differences in the lecture's amplitude for all the variables can easily be appreciated.

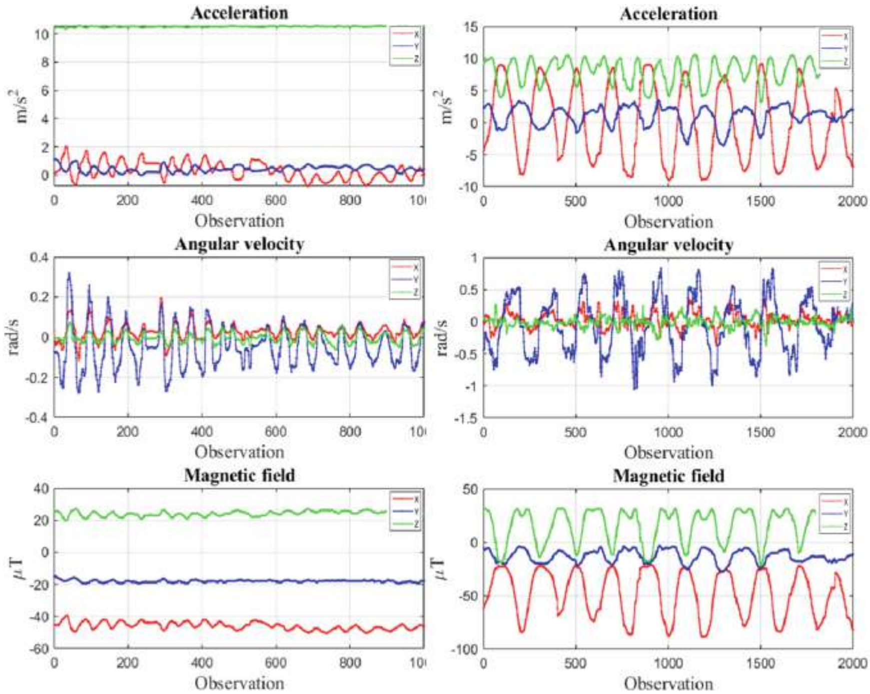
Figure 3 presents the accelerometer, gyroscope, and magnetometer readings obtained from the sensor positioned on the dorsal side of the hand, when the wrist was in a neutral, pronated, and supinated position (lectures 1–500, 500–1000, and 1000–1500, respectively).

Results obtained when classifying both datasets are shown in Table 1. The accuracy value indicates that in both cases, most of the time data can be classified correctly.

Figure 4 shows the confusion matrix obtained for the tree classifier. Figure 5 and 6 show the data obtained for the spherical grip movement. Figure 5 presents the readings obtained by the inertial sensors located on the proximal phalange of each finger and the dorsal side of the hand. In Fig. 6, there is a clear pattern corresponding to each spherical grip exerted from each force-resistive sensor by the lectures.

4 Discussion

In the case of the small wrist flexion-extension movement, the acceleration components x and y obtained by the inertial sensor located at the dorsal side of the hand was near to 0,



a) Wrist flexion-extension (−15° to 15°) b) Wrist flexion-extension (wide range)

Fig. 2. IMU data for small–wide flexion-extension movement of the wrist

while the z-axis acceleration was near 9.81 m/s^2 (Fig. 3a). Even though the component of acceleration along the x-axis was near to 0, it was the only variable that let us identify the small movements of the hand graphically. Due to the small range of movement, the angular velocity was close to 0 rad/s (Fig. 3b). In the wider wrist flexion-extension movement analysis, the lectures behaved differently: the full set of acceleration, angular velocity, and magnetic field components present a patron according to movement that can be easily identified. Even though data read from the magnetometer present a cyclical pattern corresponding to each movement exerted, careful interpretation of the movement recognition is necessary due to variations in the readings that can be obtained from the different object materials and the same movement.

When performing the flexion-extension movements in combination with pronation-supination of the wrist, patterns can also be identified from the accelerometer, gyroscope, and magnetometer data. The results obtained by analysis of the corroborated data from the different common classifiers can be categorized correctly, which could be associated with the isolation of the movements performed in a theoretical work environment. This study limitation could be solved by testing the hand mocap in common activities performed in real industrial work.

In the case of the spheric 3-finger handgrip movement, the dorsal side of the hand values do not allow an easy way to identify a patron due to the movement characteristics

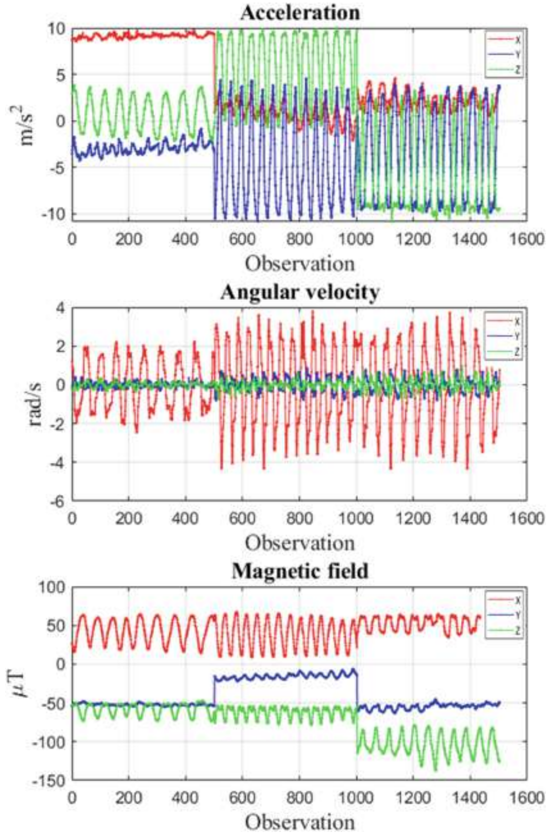


Fig. 3. IMU data for flexion-extension of the wrist with a neutral, pronated, and supinated wrist

Table 1. Classical classifiers accuracy

Classification method	Accuracy (%)	
	Small-wide FE	Pronation-supination + FE
Decision tree	**95.9**	**98.1**
Naïve-Bayes	92.4	97.6
SVM	94.5	81.9
kNN	93.5	97.5

(hand opening and closing). On the contrary, the thumb, index, middle, ring, and little finger lectures show an easy-to-identify patron in the data plot. Due to the fingertip contact with the manipulated object, the voltage measures enable identification of the

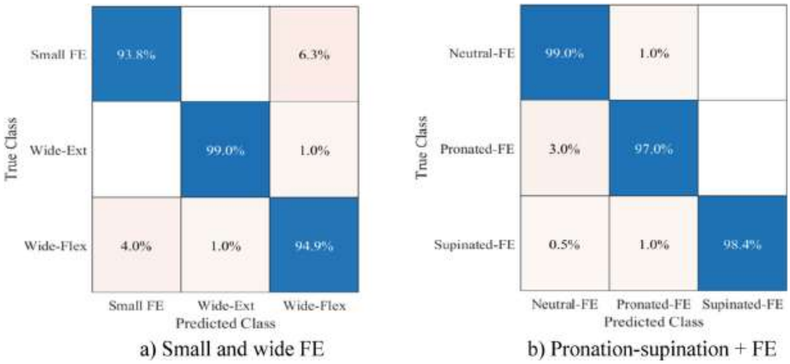


Fig. 4. Confusion matrix of the decision tree classifiers

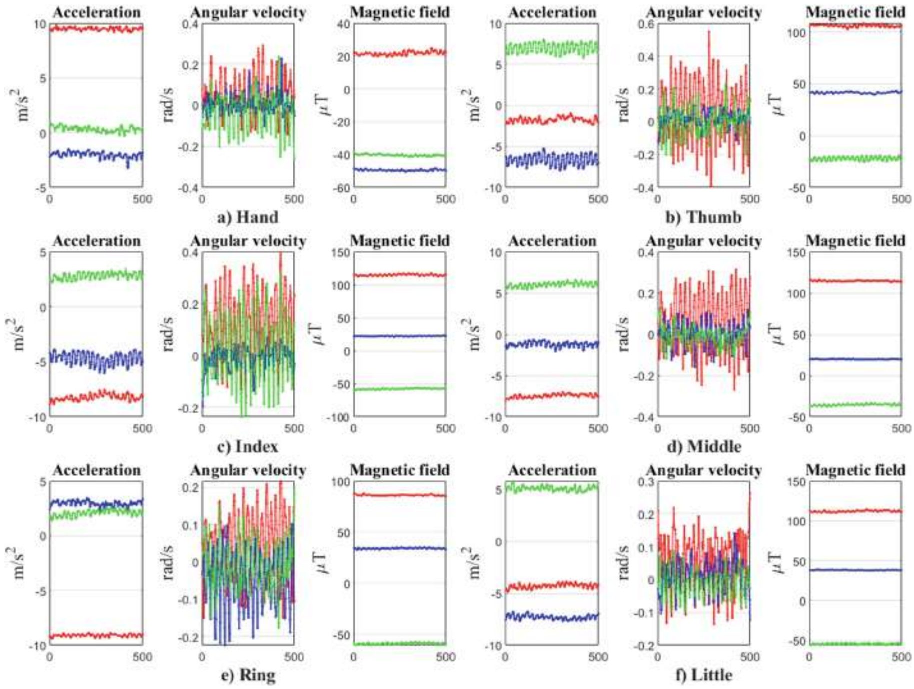


Fig. 5. IMU data for the 3-finger spherical grip

time when the force resistive sensors placed at the thumb tip and index and middle fingertips were used, and the palm, ring finger, and little finger force sensors were not.

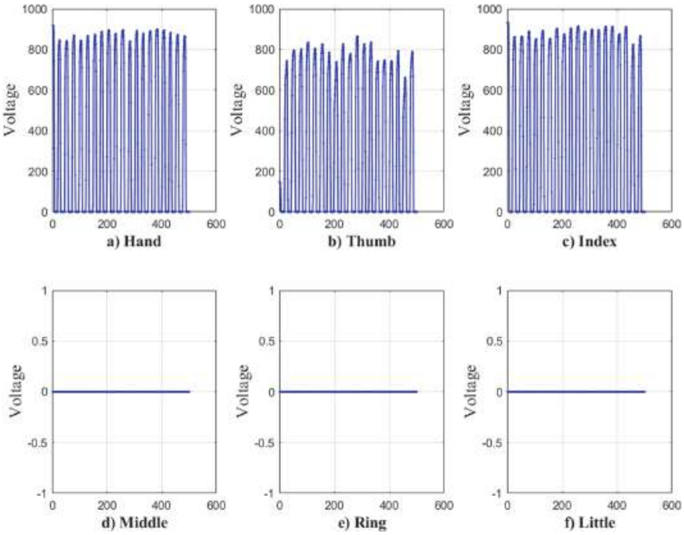


Fig. 6. Voltage value for the FSR and the spherical grip

5 Conclusions

It was demonstrated that the use of only six inertial sensors with 9 degrees of freedom and six resistive sensors are required to identify the basic movement of flexion-extension in small and large ranges of motion, as well as when identifying a pronation and supination position when flexion-extension movement is executed. Data patterns can also be found when performing a 3-finger spherical handgrip. This study can be extrapolated to the other two wrist movements, such as lateral movements, and to the common hand grasp types.

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