ISSN: 2688-8645

Wrist Motion Analysis Based on Action Detection and Pressure Sensors

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Abstract

To address the high incidence of triangular fibrocartilage complex (TFCC) injuries among fitness enthusiasts, this study proposes a wrist motion analysis method integrating object detection with flexible pressure sensing. Ulnar-side wrist pressure data were collected and, combined with Python-based key point detection, used to extract three-dimensional wrist trajectories, flexion/ulnar deviation angles, and movement velocities. A novel "pressure coefficient" metric was defined, and together with peak pressure, distribution gradient, and other features, a risk assessment model for injury was developed. A MATLAB-based biomechanical simulation system was constructed to quantify the correlation between palm pressure center shifts and TFCC injury mechanisms. This research is the first to integrate object detection with pressure sensors, enabling simultaneous motion modeling and data acquisition, providing new insights for wrist injury prevention, and enriching the theoretical framework of pattern recognition in human wrist motion analysis.

Keywords

Pattern Recognition; Pressure Sensors; Fitness; MATLAB; Pressure Threshold.

1. Introduction

Driven by the "Healthy China" initiative and the increased focus on immunity in the post-pandemic era, public fitness awareness has surged dramatically. Smart fitness equipment—such as interactive fitness mirrors, connected treadmills, smart wristbands, and fitness apps—has also experienced unprecedented popularity. Alongside this fitness boom comes a marked increase in sports injury risks. Motion deformities, compensatory force application, or uneven load distribution may reduce training effectiveness and cause muscle soreness in the short term, while prolonged accumulation can lead to chronic overuse injuries or acute sports injuries, not only hindering fitness goals but also potentially causing long-term health issues and reduced quality of life.

In recent years, pattern recognition technology has achieved continuous breakthroughs under the drive of deep learning. In motion recognition and pose estimation, graph neural networks, such as ST-GCN, have been applied to process skeleton sequence data, improving robustness by modeling spatial relationships between joints [1]. In sensor technology integration, significant progress has been made abroad. Vision-inertial fusion schemes, combining Kinect depth cameras with IMUs, effectively address occlusion issues, while methods such as HMM algorithms have achieved up to 97% accuracy in dynamic gesture recognition. Wireless sensing systems such as the Myo armband use EMG signals to detect piano finger positions and apply DTW algorithms for real-time correction, achieving 92.4% accuracy [2]. However, existing research does not address wrist trajectory recognition and application, making it difficult to identify small-range targets or assist with pushing motions in fitness training.

ISSN: 2688-8645

Moreover, recent pressure sensor research has focused on flexible wearable applications for vital sign monitoring and sports analysis. Flexible pressure sensors have made transformative breakthroughs in human health monitoring. Gao L. et al. developed an all-paper-based piezoresistive (APBP) pressure sensor using an environmentally friendly method, capable of monitoring arterial pulses and throat vibrations when placed on the skin, with advantages of low cost, eco-friendliness, simple fabrication, and high production speed [3]. A heart rate–blood pressure–blood oxygen integrated system achieved a sampling rate of 100 Hz and FDA certification [4]. However, most current research focuses on general health monitoring and does not address wrist pressure detection in fitness populations, offering no direct support for TFCC injury prevention.

To address this gap, this paper proposes using pressure sensors and object detection to prevent TFCC injuries. The research focuses on implementing early warnings and precise analysis of risky movements during fitness exercises by using object detection and pressure sensors, issuing real-time alerts for abnormal movements or excessive pressure, and quantifying wrist trajectories, joint angles, and other parameters to pinpoint the root cause of errors.

2. Method Design

2.1. Action Detection Model Construction

We first built a real-time wrist detection and tracking system based on MediaPipe to accurately locate and track wrists in video sequences. The system uses MediaPipe's hand key point detection model as its backbone, optimized specifically for hand pose estimation. The input is a wrist motion video, and the output consists of precise wrist coordinates and visual markers in the image.

Since the pre-trained MediaPipe model includes a large, diverse dataset of hand samples covering different poses, lighting, and backgrounds, our design further optimizes detection for wrist-specific key points. After wrist detection, the system extracts the two-dimensional pixel coordinates of the wrist in each frame, tracks motion across consecutive frames, and calculates wrist angles and accelerations. The lightweight, inference-optimized design of MediaPipe ensures efficient video processing.

The system also incorporates a complete video processing pipeline, including file validation, metadata parsing, frame processing progress tracking, and frame-by-frame visualization of wrist detection and skeletal structures, enhancing usability and interpretability.

2.2. Pressure Sensor Data Acquisition and Processing

A flexible pressure sensor array is attached to the dorsal side of the wrist to capture real-time pressure distributions under different postures during pressing movements. Piezoresistive sensor materials were selected for flexibility and high sensitivity. The acquisition system includes an AD conversion circuit and microcontroller. Referring to observed pressure ranges in palm/grip load experiments (45–198 kPa) and cane handle load studies and combining mechanical estimations, this study determines a reasonable range of dynamic data and risk grading [5,6]. By comparing pressures in TFCC-triggering pushing movements with those that do not induce TFCC strain, we infer potential TFCC pressure thresholds. Pressure values are collected per second during pushing movements to capture phase-specific changes, extracting pressure features for motion segmentation and intensity analysis, and proposing new threshold values.

2.3. Wrist Trajectory and Angle Analysis

The detected wrist trajectories are used to further analyze kinematic parameters. From the position sequence, the three-dimensional motion path is reconstructed, including path shape,

ISSN: 2688-8645

velocity curves, and directional changes. Using a human geometry model, wrist flexion/extension and radial/ulnar deviation angles are estimated. Features such as path length and maximum deviation describe motion characteristics, and joint models are used to deduce wrist joint angle changes.

3. Experimental Setup and Data Analysis

Table 1. Angles and accelerations of wrist movement after acquisition

Frame number	Left hand angle	Left hand acceleration
37	304.4	-3000
38	306.1	2500
39	303.9	-3479.8
40	305.9	3690.5
41	312.7	4375.6
42	314.3	-4702
43	322.8	6247.5
44	326.2	-4567.4
45	329.4	-263.8
46	331.2	-1209.6
47	333.7	611.3
48	328.9	-6560.9
49	328.7	4171.9
50	277.5	-5000
51	242.2	3500
52	246.6	4000
53	338.8	5000
54	326.2	-4500
55	330.5	3000
56	339.1	3883.3
57	338.8	-8062.9
58	340.1	1461.5
59	333.2	-7401.6
60	310.6	-4000
61	319.4	3500
62	330.2	1671.3
63	341.5	-8425.2
64	335.6	2453.2
65	335.8	-3565.7
66	335.1	-710.4
67	328.1	-5672.1
68	327.6	5765.5
69	328.2	1025.4
70	326.2	-2268.1
71	325.5	1093.4
72	324.6	-139.9
73	323	-662.8
74	319.2	-1989
75	318.2	2556
76	315.9	-1165.7
77	313.2	-370.7
78	311.6	934.6
79	309	-837.4
80	304.6	-1627.1
81	299	-1142.5
82	292.3	-889.7
83	287.4	1570.6
84	287.3	4350.4

ISSN: 2688-8645

To verify the feasibility of the proposed method, the following experimental procedure was designed:

First, wrist motion was recorded during fitness exercises, and the MediaPipe Pose model was used to extract the 2D coordinates of the elbow, wrist, and palm in each frame. From the preprocessed video frame data, the following biomechanical parameters were calculated: Wrist joint angle: using the elbow as a reference point, the angle between the wrist and forearm axis was computed (in degrees). Angle extrema: maximum, minimum, and range of angles per movement segment.

MATLAB was used to generate wrist trajectory models and corresponding angles for visualization. Abnormal wrist angles and velocities associated with TFCC injury were analyzed from the trajectories.

Table 1 shows the wrist motion angles and accelerations per frame for a pushing movement, extracted using Python.

In addition to kinematic analysis, pressure data were recorded for the TFCC region using pressure sensors to determine injury-related thresholds. Data acquisition was synchronized via timestamps or trigger signals. Analysis included: Posture extraction errors: effect of detection model inaccuracies on trajectory reconstruction. Pressure–angle relationship: sensor output trends under different load conditions. Movement feasibility: proposing reasonable pressure thresholds from experimental data.

Table 2. Shoulder Angle and Risk Level by Phase During a Bench Press

Timestamp	Phase Description	Shoulder Angle	Risk Level
0	Starting Hold	5	SAFE
1	Descent Initiation	70	CAUTION
2	Approaching Chest	130	MODERATE RISK
3	Explosive Push (Peak)	195-205	HIGH RISK
4	; Mid-Push Phase	160	HIGH RISK
5	Approaching Lockout	90	CAUTION
6	Completion / Reracking	10	SAFE

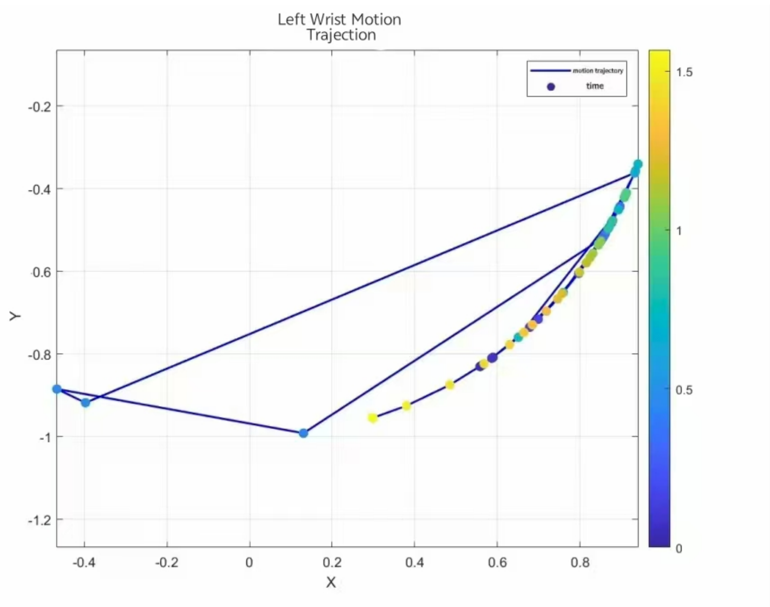

Figure 1. Left Wrist Motion Trajectory

Table 2 presents pressure data during a pushing motion. At approximately the 3-second mark, peak pressure reached 196 kPa—within the high-risk zone—consistent with literature values [5,6].

Angular velocity and acceleration curves were derived from continuous joint angle and pressure analysis to evaluate smoothness and force. A MATLAB-based template motion trajectory model was constructed, as shown in Figure 1.

4. Research Results

From the recorded left wrist trajectories and the biomechanics of TFCC injuries, several key injury risk factors were identified:

4.1. Extreme Angle Exposure:

242.2° (frame 51) likely corresponds to excessive radial deviation, stretching the TFCC; angles between 330°–340° correspond to excessive ulnar deviation, directly compressing the TFCC between the ulna and carpal bones—classic high-risk positions. Rapid switches between extremes (e.g., frame 50–53: 277.5° to 338.8°) increase instantaneous TFCC pressure.

4.2. High Acceleration and Abrupt Load Changes:

Multiple instances exceeded ±4000°/s^2 (e.g., frame 43: 6247.5°/s^2; frame 48: -6560.9°/s^2; frame 63: -8425.2°/s^2), surpassing the TFCC tolerance (~±3000°/s^2) and generating high shear forces. Frequent acceleration reversals, such as frame 37 (-3000°/s^2) → frame 38 (2500°/s^2) → frame 39 (-3479.8°/s^2), alternate between tensile and compressive loads, leading to cumulative microdamage.

4.3. Trajectory Instability and Abrupt Directional Changes:

Successive spikes (5000°/s^2 → 3500°/s^2 → 4000°/s^2 → 5000°/s^2) indicate “sudden stop–reverse” patterns—classic acute TFCC injury mechanisms. Jagged trajectory segments suggest poor motion buffering, further raising risk.Summary of key risks: extreme angles, high acceleration, and abrupt load changes act synergistically—matching clinical TFCC injury mechanisms. Acute injury risk: sudden movements in frames 50–53 may cause TFCC tears. Chronic injury risk: repeated >330° ulnar deviation compresses the TFCC, while frequent acceleration reversals cause cumulative microdamage.

4.4. Recommendations:

Limit ulnar deviation to ≤300° to reduce direct TFCC compression. Reduce motion acceleration—avoid >±3000°/s^2—by smoothing transitions. Improve motion smoothness with gradual angle changes. Strengthen surrounding muscles (extensor/flexor carpi ulnaris) to share TFCC load. Avoid excessive pressure on the TFCC region. Conclusion and Prospects

This paper proposes a wrist motion analysis method combining vision-based action detection with flexible pressure sensing. By integrating a MediaPipe-based wrist detection model with wearable pressure sensors, a motion model for TFCC-inducing pushing actions was built, along with a specific pressure threshold. The method enables comprehensive analysis of wrist motion and pressure. Results show that flexible pressure sensors can monitor wrist loading in real time and, when combined with simple models relating pressure to joint angles, provide valuable auxiliary information for motion recognition and health monitoring.

5. Limitations:

Data diversity: limited sample size, mainly healthy males; lacks female subjects, TFCC recovery patients, and varied body types.

ISSN: 2688-8645

Movement variety: only one type of pushing action analyzed; no coverage of high-risk exercises such as bench press or snatch.

Sensor precision: piezoresistive sensors have limited linearity and repeatability; dynamic pressure drift and measurement errors (e.g., 196 kPa peak) not quantified; low array density limits spatial resolution of "pressure coefficient."

Environmental factors: effects of temperature and sweat on sensitivity, as well as long-term wear stability, remain unverified.

6. Future Work:

Expand dataset to >100 participants with diverse demographics and injury histories. Include multiple fitness movements. Use high-linearity piezoelectric film arrays to improve resolution in the TFCC ulnar region.

Acknowledgments

I sincerely thank Professor Xu Han for his invaluable guidance and support throughout the design and implementation of this project. His insights in visual algorithm framework design and wrist tracking optimization, as well as parameter tuning for detection thresholds and matching strategies, significantly improved trajectory stability. His rigorous academic approach and engineering expertise have greatly benefited me.

Professor Xu's suggestion to build a simulated motion model in MATLAB ensured robust visualization analysis. His detailed feedback on paper writing and documentation helped me present system design and results more clearly. His dedication to combining theory with practice has deeply influenced my research approach.

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