

Design and build of an affordable DIY system for field motion capture: a volleyball spike field test

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Abstract

Motion capture is widely used to refine sports technique and to guide recovery from injury, but laboratory systems are bulky and too expensive for most hobby athletes, schools and clubs. We designed an open-source kit that pairs a wrist-worn inertial sensor, built from an Arduino Nano 33 BLE, with a smartphone camera processed by MediaPipe Pose, and tested it on 139 volleyball spikes from 12 players outdoors. The wrist unit costs 40 USD in consumer parts and can be assembled with basic tools. The camera channel tracked the hitter in every analysed spike and met its frame-timing thresholds in 95 percent of them. The wrist sensor delivered a usable stream in 42 of the 135 analysed spikes, at 53 to 92 samples per second, and resolved swings near 2000 degrees per second; most of the losses arose in the Bluetooth streaming chain rather than in the sensor itself. The camera-derived elbow and wrist features took values in a plausible range across the dataset. These results show that the system can record a complex whole-body movement outdoors, that the wrist sensor delivers high-rate data when its stream arrives intact, and that the camera channel alone yields arm features in a plausible range. They also point to local data logging as the change most likely to make the sensor channel as dependable as the camera. We publish a blueprint for the build together with the data and code.

Keywords: open hardware, low-cost motion capture, wearable sensors, inertial measurement unit, markerless pose estimation, Arduino, volleyball, sports biomechanics, education

1. Introduction

In sport, wearable sensors and motion analysis can give coaches and athletes objective information on workload and technique, and reviews suggest that such information can support performance and injury-risk management [1]. Movement patterns measured in the laboratory have been associated with later injury; in one prospective study of female athletes, knee loading during a landing task predicted subsequent anterior cruciate ligament injury [2]. In rehabilitation, sensors that report movement back to the patient in real time can provide a form of biofeedback, and a review of the field identified inertial sensors as the most widely researched form of biomechanical biofeedback [3]. The same measurements that guide an elite athlete might therefore help a school team train safely or a patient recover after injury.

However, access to these benefits is unequal. Optical marker systems and inertial suits are listed at prices from several thousand to well over one hundred thousand US dollars (Supplementary Table S2), and they typically need trained staff and dedicated space to run. In markets such as Vietnam, where to our knowledge no commercial sport-biomechanics product is sold at a hobbyist price and specialist suppliers of research-grade hardware are few, this cost gap can keep movement measurement out of reach of school teams, community clubs and student research projects. Two developments now appear to make low-cost alternatives possible. The first is the miniaturisation of inertial sensors: small inertial measurement units

(IMUs), chips that measure acceleration and rotation, now cost a few dollars and fit on a hobby microcontroller board, and a systematic review documents their widespread use for in-field sport analysis [4]. The second is markerless pose estimation: machine-learning software that returns the positions of a person's joints from ordinary video, without markers or special cameras [5], [6], and whose accuracy against marker-based capture is being evaluated, with mixed results, for clinical and sporting movements [7], [8].

Importantly, open, do-it-yourself instruments have been proposed as a route to wider access. Building research equipment from open-source hardware has been reported to cut its cost substantially while letting users adapt and repair it [9], and it has been argued that when high-technology instruments can be reproduced cheaply and distributed at scale, measurement need no longer be confined to well-funded laboratories, which would open the door to community and population-level science projects run by schools, clubs and clinics [10]. In sport science, a low-cost smartphone application for jump height has been validated against a laboratory force platform [11]. A wrist sensor and phone camera that a student can build could therefore extend this approach to whole movements, and might give schools a practical way to teach electronics, programming and biomechanics together.

Here, we describe such a kit and test it in the field. Four design parameters guided the work. The system had to be cheap, with parts costing tens rather than thousands of US dollars; scalable, so that a school or club could build several units from the same files; reproducible with tools a student can reach, including a 3D-printed enclosure and ready-made electronic modules joined by a handful of soldered wires; and safe to build and wear, with a small, protected battery and no exposed high-energy parts. These parameters led to a two-channel design. The wrist unit is built around the Arduino Nano 33 BLE, a hobby microcontroller board that carries a Bluetooth radio and an inertial sensor on one circuit board, so that the only electronics to add are a battery, a charging module and a switch. The video channel is a smartphone camera, which most users already own, processed with MediaPipe Pose, free software that extracts joint positions from ordinary video [12], [13]. A laptop records both channels on one clock, which removes the need for manual synchronisation.

We chose the volleyball spike as the test movement for three reasons. First, it is a complex whole-body skill: kinematic studies describe approach, jump, trunk rotation, arm cocking and forward swing following one another in a proximal-to-distal sequence within about a second, so a single recording exercises both the camera, which must follow the whole body, and the wrist sensor, which must resolve the final swing [14], [15], [16]. Second, it is among the more demanding movements a wearable can meet: published kinematics show the hand reaching ball contact at high speed with an abrupt impact, which stresses the sampling rate, the synchronisation of the two channels and the range of the accelerometer at once, so that a kit that records the spike can be expected to cope with most slower movements [14], [15]. Lastly, the spike matters for health and participation: volleyball is reported to have one of the highest participation rates of any sport, an elite player has been estimated to perform some 40,000 spikes in a season, and the cumulative shoulder load from spiking and serving has been linked to shoulder pain, reported as the third most common injury in the game [17]. A low-cost way to record spiking technique could therefore be useful to a large number of players and coaches, for whom manual video digitising with free tools such as Kinovea is the usual low-cost alternative, at the cost of human effort for every frame [18].

We show that this system can be built for 40 USD with basic tools, that its camera channel reliably tracks the whole body through the spike outdoors, that its wrist sensor resolves the timing and intensity of the swing at up to about 90 samples per second whenever its stream arrives, and that the camera channel yields elbow and wrist features with plausible values, and we identify the changes that we expect to make the sensor channel as dependable as the camera. Taken together, these results establish the feasibility and basic capability of the system and provide a blueprint on which more complex versions can be built. The complete build guide is given in Supplementary File S1.

2. Methods

2.1 Kit design

A full build guide, with the bill of materials and suppliers, wiring, assembly steps, firmware, software and settings, is given in Supplementary File S1. In brief, the kit has three parts: a wrist unit that is built, and a smartphone and a laptop that most users already own.

The wrist unit is a small case strapped to the forearm just above the wrist of the hitting arm. Inside it, an Arduino Nano 33 BLE board [19] carries both the computer and the motion sensor, an LSM9DS1 chip [20], read through an open-source Arduino library [21], that measures acceleration along three axes and rotation rate about three axes. A 200 mAh rechargeable battery powers the board through a small charging and voltage-conversion module, with a switch and a USB-C socket for charging. These parts sit in a 3D-printed plastic case of 130 by 22 by 8 mm. Assembling one unit means soldering seven wires between ready-made modules and printing the case; the parts cost 40.02 USD (Table 1).

A short program on the board reads the sensor 100 times per second by design and sends the readings to the laptop over Bluetooth. The smartphone, on a tripod, acts as a webcam connected to the laptop by cable. A Python program on the laptop records the sensor stream and the video together and stamps both with the laptop's clock, so that the two are aligned without any manual synchronisation. After each recording the program runs MediaPipe Pose [12], [13], free software that finds a person's joints in ordinary video, and saves the positions of the right shoulder, elbow and wrist in every frame, so the pipeline assumes a right-handed hitter.

2.2 Bench test

Before field use, the accelerometer was checked against gravity by recording the unit at rest with each axis pointing up and down in turn and comparing the measured acceleration magnitude with 1 g. Gyroscope bias and drift were measured from a 10-minute recording at rest. No calibration was applied.

2.3 Participants and field protocol

Twelve volleyball players took part: five professional players from a club squad in Ho Chi Minh City and seven amateur players from university and recreational teams, coded P1 to P5 and A1 to A7. The study was a minimal-risk student research project with no intervention beyond wearing the wrist unit during normal spiking practice; Two Sigma Lab reviewed the protocol, classified it as minimal risk and waived formal ethics board review, and participants gave written informed consent (see Declarations).

Recording took place outdoors on a standard court in eight sessions (S1 to S8) between 15 June and 22 August 2026. The unit was strapped to the back of the forearm just above the wrist of the hitting arm. The phone stood on a 2 m tripod at the midpoint of the net, about 0.5 m from it, with the optical axis parallel to the net, so that the hitter was seen from the side at about 4.5 m. Players performed self-paced spikes from their usual approach against balls tossed by a partner. In five recordings the first attempt failed and the player repeated the spike within the same recording; the completed spike was the one analysed. Ball contact was marked on the video by one rater, and four recordings in which the video ended before a contact frame could be marked were excluded, leaving 135 of 139 for analysis.

2.4 Quality control and outcomes

Each recording passed through an automated decision tree for each channel (Table 2; Figure 2b). The camera channel was usable when the video was present, the skeleton visibly tracked the hitter through the spike, and the effective frame rate was at least 25 frames per second with no gap longer than 100 ms. The wrist sensor channel was usable when the file was present, the effective sampling rate was at least 30 Hz with packet loss of at most 50 percent of the 100 Hz design rate, and the signal showed motion (peak acceleration at least 2 g and peak angular velocity at least 100 degrees per second). From the camera data,

eight features of the hitting arm were computed for every analysed recording over an arm-swing window that runs from the frame of greatest elbow extension in the 1.5 s before contact to the contact frame; in a spike this frame normally precedes arm cocking, so the window spans the cocking of the arm and the forward swing. The features are the elbow angle at ball contact and at the start of the window, the elbow range of motion over the window, the mean elbow angular velocity over the window, the wrist path length, net displacement and peak speed over the window, each divided by the upper-arm length in the same recording, and the duration of the window. These are planar quantities in normalised image coordinates from a single uncalibrated camera; their definitions are given in Supplementary File S1, Section S1.11. The outcomes were the cost and complexity of the build, the bench accuracy, the proportion of usable recordings in each channel, the range of signals captured, and the distributions of the camera-derived features.

2.5 Data analysis

All quantities were computed in Python 3.10 with NumPy [22] and pandas [23], and figures were drawn with Matplotlib [24]; the scripts are released with the data. For the bench test, the acceleration magnitude in each of the six orientations was the mean over the middle half of each stable segment, and the error was its difference from 1 g; gyroscope drift was the magnitude of the angle obtained by integrating the three angular rates over the 10-minute recording, with and without subtracting the mean rate over the first 5 s. For each field recording, the effective sampling rate was the number of sensor samples divided by the time between the first and last sample on the board's own clock; packet loss was the shortfall against the 100 Hz design rate; a sample was counted as clipped when any axis reached the ceiling of the configured range; and peak acceleration and angular velocity were the largest magnitudes of the three-axis vectors. The sensor library converts gyroscope counts at a scale about 13 percent below the datasheet sensitivity, and all angular velocities in this paper are reported in that library scaling (Supplementary File S1, Section S1.4). Camera frame rate and frame gaps were computed from the laptop timestamps of the saved frames, and MediaPipe landmarks were smoothed with a Savitzky-Golay filter [25] (order 2, window about 0.1 s) before features were computed.

To check whether usable sensor recordings had sampled the swing itself, we placed the video-marked contact on the sensor clock for the usable recordings from S5 and S7, in which the laptop and board clocks agreed to within 0.6 s over a recording. The camera start was taken as the arrival time of the first sensor sample minus the logged start-time offset between the two streams, the board clock was anchored to the laptop clock by the least-delayed notification, and we recorded whether the stream spanned the contact, the largest gap between samples within 0.5 s of contact, and the time of the largest acceleration peak relative to contact. Recordings from S1 to S4 were left out of this check because their arrival-time and board-time spans differed by up to 1.7 s, which made the placement unreliable.

Results are reported as counts and percentages of recordings, and as medians with interquartile ranges, because most distributions were skewed. The analysis is descriptive throughout: no inferential comparisons were made, because the professional and amateur players were recorded in different sessions with different sensor settings, so that any difference between groups could not be separated from differences between sessions.

3. Results

One unit costs 40 USD and needs seven wired connections

To test whether the kit meets the first design parameter, affordability, we recorded the cost and source of every part and the steps needed to assemble one unit. One wrist unit required eight purchased components costing 40.02 USD, of which the Arduino board accounted for 86 percent (Table 1). Importantly, all parts were bought from consumer electronics shops and online marketplaces, and the case from a local 3D-printing service for 0.38 USD, so no specialist supplier was needed. Assembly needed a soldering iron, wire

stripper and multimeter, and consisted of seven wired connections, each verified with the multimeter or the board's LEDs before the next (Supplementary File S1, Section S1.3). The finished unit weighs about 20 g and runs for about 50 minutes per charge, enough for a typical training session; both figures were estimated from the session logs rather than measured. This meets the cost and reproducibility parameters set out in the Introduction. Figure 1 shows the unit, how it is worn, the court set-up and the spike itself.

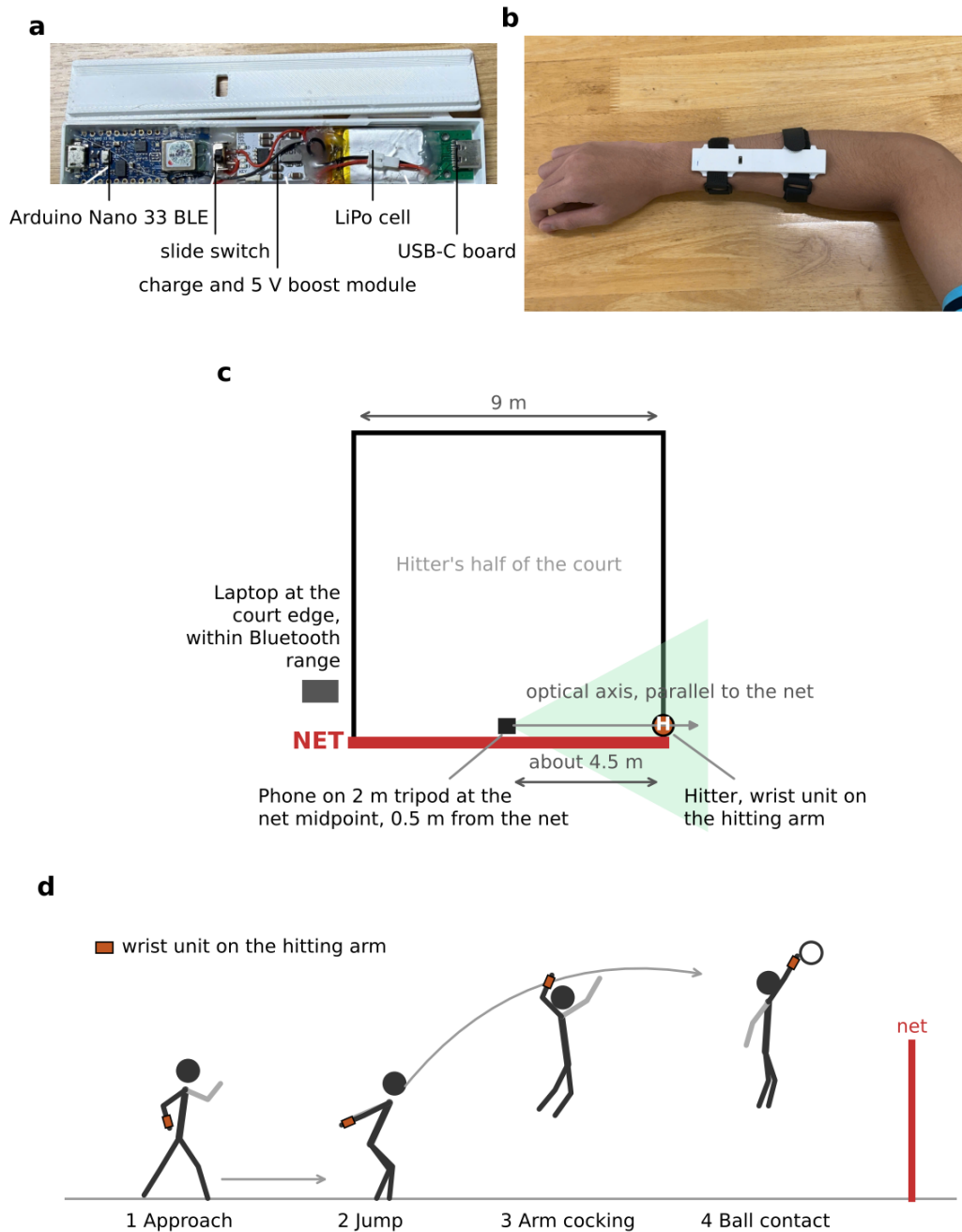


Figure 1. The kit and the field test. (a) The wrist unit with its lid removed, components labelled. (b) The unit strapped to the forearm just above the wrist. (c) Court set-up, top-down view: the phone on a 2 m tripod at the net midpoint, 0.5 m from the net on the hitter's side, with the optical axis parallel to the net; the hitter spikes about 4.5 m from the camera and the laptop stays at the court edge within Bluetooth range. (d) The volleyball spike as the camera sees it: approach, jump, arm cocking and ball contact follow within about one second, with the wrist unit (orange) on the hitting arm throughout.

The accelerometer reads gravity to within 5 percent on average without calibration

Before taking the kit onto the court, we needed to know whether the sensor built into a hobby board, read by hobby firmware, reports acceleration correctly without any calibration, since a builder following the guide will have no reference instrument. We therefore recorded the unit at rest in six orientations and compared the measured magnitude with gravity. The measured acceleration magnitude ranged from 0.910 to 1.076 g, with a mean absolute error of 44.8 mg (4.5 percent) and a maximum of 90.1 mg (Table 3; Figure 3a). Most of this error came from a constant offset of about 0.08 g on one axis, which read 0.910 g pointing up and 1.076 g pointing down, so a per-axis offset correction would remove most of it. These errors match the sensor's typical zero-g offset of 90 mg [20], so the sensor behaves as its datasheet promises and the firmware converts its output correctly. In the same way, we integrated the gyroscope over 10 minutes at rest to see how far its output drifts: after removal of the initial bias the drift was 16.1 degrees per minute (Figure 3b). In our reading this is adequate for the timing and peak measures that the kit is designed to deliver, while orientation tracking would need sensor fusion.

The camera tracked every spike and met timing thresholds in 95 percent

We next sought to determine what each channel delivered under real conditions, since a kit that works on the bench but fails outdoors would not meet its purpose. The camera channel produced a skeleton that tracked the hitter through the spike in all 135 recordings, and 128 (95 percent) met both frame-timing thresholds (Figure 2b; Figure 3c). All seven exceptions came from the first four sessions in June and early July (five in S1, one in S2 and one in S4), and all seven were among the 17 recordings in those sessions that were filmed from an alternative camera position; the operator attributed the frame drops to the laptop overheating, which was not measured. The camera position described in the Methods was used for every recording from S5 onwards, and every one of those met both thresholds. Achieved frame rates clustered near 60 frames per second in some sessions and near 40 in others. These results suggest that the camera channel is dependable once the camera position is fixed, and that it needs no calibration object or markers to track a fast whole-body movement outdoors.

The wrist sensor delivered a usable stream in 42 recordings

The wrist sensor is the channel that the camera cannot replace, because it samples the swing faster than any phone camera, so its yield and the signals it captures decide whether the two-channel design is worthwhile. In contrast to the camera, the wrist sensor delivered a usable stream in 42 recordings, each at 53 to 92 Hz, and 38 recordings had both channels usable (Figure 2b; Figure 3c, d). Figure 2c shows a typical spike: acceleration and angular velocity rise through the approach and arm swing and peak together at ball contact. Importantly, across the usable recordings, peak acceleration at impact sat at the ceiling of whichever range was set: about 6 g at the 4 g setting, about 14 g at 8 g, and 18 to 39 g (median 35 g) at the 16 g setting, beyond the sensor's specified range, so these peaks show that the range was exceeded rather than the true impact (Figure 3f). Angular velocity came close to the gyroscope's 2000 degrees per second range on a single axis and reached about 2570 degrees per second in magnitude, in the library scaling described in Section 2.5. However, of the remaining 93 recordings, 54 lacked a file and 33 fell below the throughput threshold (Figure 3d, e), mostly in whole sessions, which points to the Bluetooth connection at the start of a session rather than to the sensor itself (Supplementary Table S3); the other six, all from a spare unit used for one player during a six-minute window in S7, streamed normally but read rest values throughout, and the fault was not diagnosed.

Because the throughput check covers the whole recording, a usable label does not by itself show that the swing was sampled: the longest stall inside a usable recording ranged from 45 to 932 ms (median 402 ms), which is long enough to swallow a forward swing. We therefore placed the video-marked contact on the sensor clock for the 31 usable recordings from S5 and S7 (Section 2.5). The stream spanned the contact in all 31, and the largest acceleration peak fell within 0.3 s of it in 23, which supports the shared-clock alignment. In 11 recordings, however, a stall longer than 100 ms fell within 0.5 s of contact, and in seven of them it

covered the final 0.3 s before contact or the impact itself. Eight recordings had their largest peak 0.7 to 2.9 s away from the marked contact rather than at it, and six of these were among the 11 with a stall near contact, which suggests that the impact itself had fallen inside the stall. Taken together, these findings suggest that when the stream arrives the sensor resolves the swing in the detail the design intended, that the losses sit in the streaming chain between the board and the laptop, which is the part of the design most easily replaced, and that a check of the samples around contact belongs in the quality control of future versions. Figure 3 brings the performance measures together.

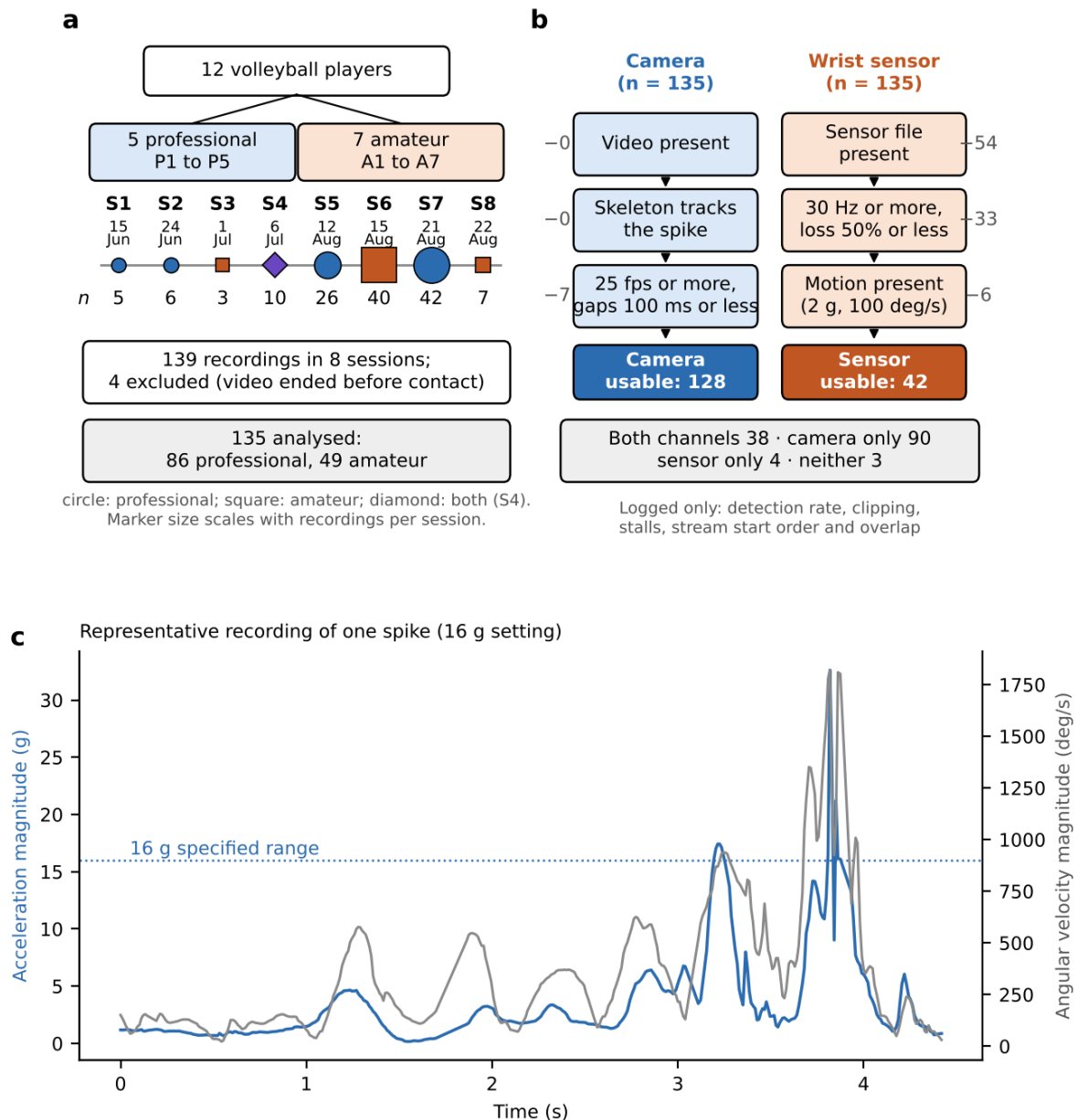


Figure 2. Field test design, quality control and a typical recording. (a) Players, sessions and recordings: 12 players, eight sessions with the number recorded in each, 4 recordings excluded because the video ended before a contact frame could be marked, 135 analysed. (b) Quality-control checks applied in order to each channel, with the number of recordings removed at each step. (c) Acceleration magnitude (left axis) and angular velocity magnitude (right axis) through one representative spike from the wrist unit; the dotted line marks the sensor's 16 g specified range.

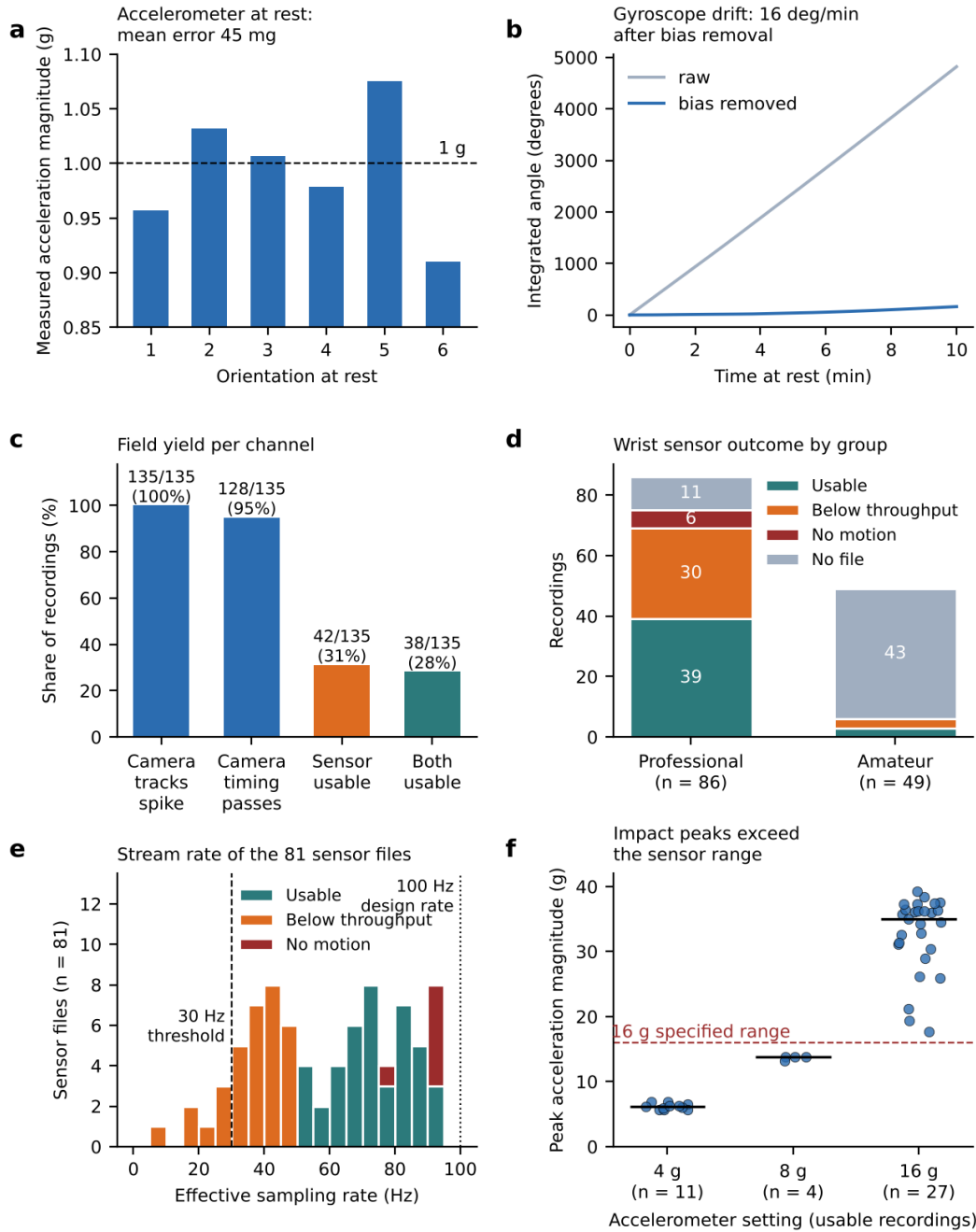
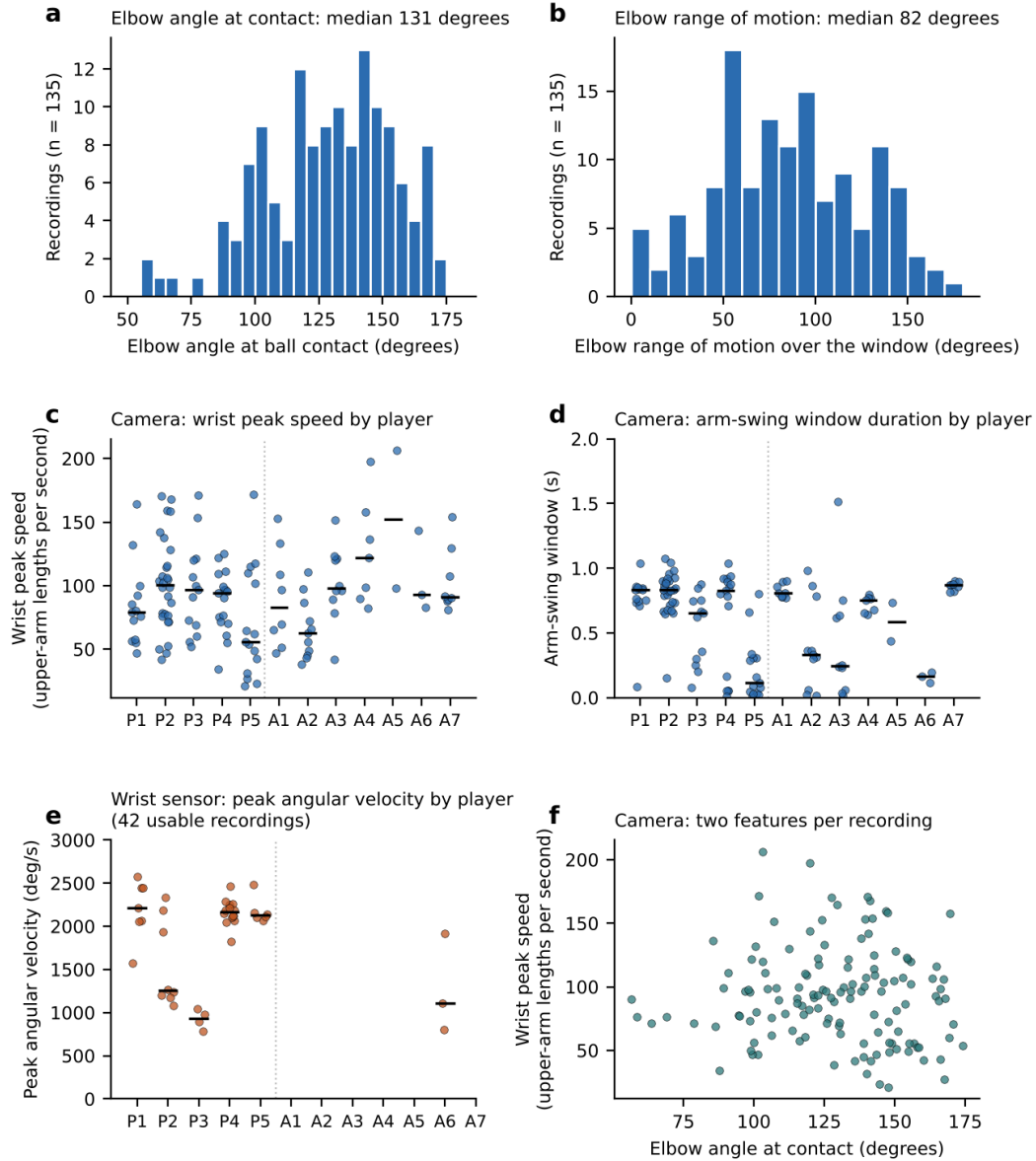


Figure 3. Performance of the kit on the bench and in the field. (a) Acceleration magnitude measured at rest in six orientations against the 1 g reference. (b) Angle obtained by integrating the gyroscope over 10 minutes at rest, raw and after subtracting the bias measured in the first 5 s. (c) Share of the 135 analysed recordings in which the camera tracked the spike, the camera met the frame-timing thresholds, the wrist sensor delivered a usable stream, and both channels were usable. (d) Wrist sensor outcome by player group. (e) Effective sampling rate of the 81 recordings that produced a sensor file, coloured by outcome, with the 30 Hz threshold and the 100 Hz design rate. (f) Peak acceleration magnitude in the 42 usable recordings by accelerometer setting, with medians; the dashed line marks the sensor's 16 g specified range.

The camera channel yields arm features in a plausible range

Having established that both channels deliver usable signals, we asked whether the camera channel also yields the kind of quantities a coach or physiotherapist would want, since a tracked skeleton has little value

unless it can be turned into measures of the movement. We therefore examined the distributions of the eight camera-derived features across the 135 analysed recordings (Figure 4). The elbow angle at ball contact had a median of 131 degrees (interquartile range 112 to 148), with 102 of 135 recordings between 100 and 160 degrees, and the elbow was close to full extension at the start of the arm-swing window (median 175 degrees). Elbow range of motion over the window had a median of 82 degrees (55 to 116), the wrist's peak speed a median of 92 upper-arm lengths per second (66 to 113), and the window a median duration of 0.75 s (0.30 to 0.85). Players differed in their medians (Figure 4c, d), and recordings from the same player clustered. However, in 33 recordings the window was shorter than 0.3 s, 16 of them from two players (P5 and A3), and in 19 of these it was shorter than 0.1 s, which at 40 to 60 frames per second is one to six frames: there the rule had locked onto an extended-arm frame just before contact rather than the position before cocking. The window was longer than 1.5 s in a further three recordings, and the single largest wrist peak speed, 206 upper-arm lengths per second, came from a recording in which the tracker had followed the wrong arm until 0.5 s before contact, so it is probably an artefact of the switch between arms. We read these results as showing that the pipeline produces values in a plausible range for the arm at contact and over the swing, and that the rule that finds the start of the window is the weakest link in the feature set. Because the features are planar projections from one uncalibrated camera and have not been compared with a reference system, we present them descriptively and do not compare players or groups.



P1 to P5 professional, A1 to A7 amateur; black bars are player medians. Camera features are planar, unvalidated image-space quantities.

Figure 4. Camera-derived features across the 135 analysed recordings. (a) Elbow angle at ball contact. (b) Elbow range of motion over the arm-swing window. (c) Wrist peak speed, in upper-arm lengths per second, by player. (d) Duration of the arm-swing window by player; values under 0.3 s reflect a failure of the rule that finds the start of the window rather than a short swing, and two values above 2 s lie beyond the axis. (e) Peak angular velocity from the wrist sensor by player, for the 42 usable recordings, in the library scaling described in Section 2.5. (f) Elbow angle at contact against wrist peak speed, one point per recording. P1 to P5 are professional and A1 to A7 amateur players; black bars are player medians. All camera features are planar quantities in normalised image coordinates from a single uncalibrated camera.

4. Discussion

A student or amateur can build the kit with basic tools

The first question a reader will ask of a DIY design is whether anyone outside the authors' workshop can reproduce it. The kit was designed and built as a student research project, and we expect every part of it to be within reach of a motivated secondary school student or amateur with adult supervision, although this has not yet been tested with independent builders. The parts are sold in consumer shops and online marketplaces for 40 USD. The tools are a soldering iron, a wire stripper and a multimeter, which many school design and technology departments are likely to own, and the case can be printed at a school, makerspace or print service. The electronics need seven wired connections between ready-made modules, with no circuit design and no surface-mount soldering, and each step has a simple check. The software runs on an ordinary Windows laptop with free tools, and the firmware is a single short Arduino sketch. Supplementary File S1 sets this out as numbered steps with photographs, wiring and safety notes. The natural next step is a timed build by students who have not seen the device, which would turn this design claim into a measured one.

The camera, the shared clock and the wrist sensor deliver the core measures

The second question is what a builder gets for the effort. Three parts of the kit work well as built, and together they establish the basic functionality of the system. The camera channel proved the most reliable part in our hands: a phone on a tripod and MediaPipe Pose tracked every spike outdoors, without markers or a calibration object, and set-up takes a few minutes. The shared clock made synchronisation automatic in this study: video frames and sensor samples are stamped by the same laptop, so no clap, flash or manual alignment is needed, and placing the video-marked contact on the sensor clock put the acceleration peak within 0.3 s of it in 23 of 31 recordings, which is a first, approximate check that the alignment holds. The wrist sensor, when its stream arrives without a stall across the swing, can capture what a camera at 30 to 60 frames per second cannot: the timing and intensity of the swing at up to about 90 samples per second, with readings that agreed with gravity to within 5 percent on average at rest. From the tracked skeleton, the pipeline produced elbow angles and wrist speeds with values in the range expected for a spike, and recordings from the same player clustered. Together these appear to cover the uses most relevant to coaching, teaching and rehabilitation at this cost: seeing the movement, timing its phases, detecting when and how hard it happened, and putting first numbers on the arm action, although which measures matter most in practice remains to be established with users.

Four changes would make the kit more dependable

However, the field test also points to four challenges, each with a plausible solution. The largest is data transfer: streaming every sample over Bluetooth ties the sensor channel to the link and to the firmware that services it, most incomplete recordings arose there, and even in usable recordings a stall sometimes fell across the swing itself. Buffering samples on the device and re-requesting lost packets has been shown to reduce such loss in healthcare wearables [26]; writing samples to onboard memory and using Bluetooth only to start and stop recording would remove the dependence altogether, although we have not yet tested this, and a check of the samples around contact should be added to the quality control either way. The second is sensor range: spike impacts exceed the LSM9DS1's 16 g specification [20], so measuring peak impact would need an additional high-range accelerometer of 100 to 200 g. The third is camera consistency: fixing and recording the camera position and frame rate, and placing a known length in the scene, should allow image measurements to be converted to metres. The fourth is validation: the camera-derived arm angles and wrist distances are planar projections from one uncalibrated camera, the rule that finds the start of the arm-swing window failed in about a quarter of recordings (Figure 4d), and comparison with a reference system is needed before any feature is used to judge technique [7], [8], [27]. The firmware also gained from smaller changes during the study, such as a wider accelerometer range and more frequent servicing of the Bluetooth stack, which are recorded in Supplementary File S1 so that builders start from the final version.

The kit scales in cost, numbers and reach

Finally, the kit appears well placed to scale in cost, in numbers and in reach. Each additional wrist unit costs 40 USD, so a set of ten for a school team or class costs about the same as a single commercial jump sensor package (Supplementary Table S2), and the software and processing pipeline are free. Quality control is fully scripted, so the effort of checking data grows little as the number of recordings rises; this study processed 139 recordings with one operator. With local logging, each athlete could wear a unit and record independently, and one phone and laptop could serve a whole session; a single laptop can also hold Bluetooth connections to several units at once, which we have not yet tested. Because the hardware files, firmware and software are open, groups elsewhere should be able to build, adapt and translate the kit for their own sports and languages. The main constraint on scale is supply: the original Nano 33 BLE is being replaced by a revision with a different IMU [19], so the firmware will need a small update for new builds, and other boards with the same Bluetooth chip and an onboard IMU offer alternatives. Beyond volleyball, the same placement is likely to suit other overhead actions such as the badminton smash and handball throw, and the unit moved to the ankle or lower back could in principle time jumps, landings and gait, although neither has been tested.

Limitations of this study

Several limitations should be noted. This is one kit tested over one summer with twelve players performing tossed-ball practice spikes rather than game attacks. The bench test covered the accelerometer at 1 g on one unit, battery runtime and mass were estimated, the sensor channel was characterised mainly on professional players, and the build has not yet been timed with independent builders. The camera-derived features are unvalidated and the rule that finds the start of the arm-swing window is unreliable, ball contact was marked by one rater, the quality thresholds were set by the team rather than derived from a validation study, and 17 recordings in the first four sessions were filmed from an alternative camera position that was not documented. Participant sex, age, playing experience and handedness are not reported, and because the pose software saved the right-arm landmarks the analysis assumes right-handed hitters. The check of the samples around contact rests on the start-time offset logged by the capture software, which was not verified against an independent event, so its counts are approximate.

5. Conclusion

In conclusion, a wrist sensor and a smartphone, assembled from 40 USD of consumer parts with basic tools, recorded a movement as fast as the volleyball spike outdoors. The camera channel did so reliably as built and yielded elbow and wrist features with values in the range expected for a spike, the wrist sensor captured the swing in detail when its stream arrived without a stall across it, and local logging and a validated rule for the start of the arm swing appear to be the most promising next steps. Releasing the full build guide, data and code makes the kit available to the schools, clubs and clinics that may benefit most from movement analysis and can least afford a laboratory system.

Declarations

Author contributions. N.M.K.N., S.R.P. and T.H. designed the study together. N.M.K.N. built the kit, carried out the bench and field experiments, collected and contributed the data and performed the basic data analysis. N.M.K.N. wrote the build guide (Supplementary File S1) and contributed to the Methods and the Introduction. T.H. and S.R.P. wrote the rest of the paper.

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Ethics and consent. The study was a minimal-risk, non-interventional student research project. Two Sigma Lab reviewed the protocol, classified it as minimal risk and waived formal ethics board review. All

participants gave written informed consent to video recording and to the public release of their session dates and sensor data. The released files identify players by code only, and raw video and images are not shared.

Data, code and hardware availability. The build guide (Supplementary File S1), the supplementary tables, the figures and the analysis scripts are available in the supplementary materials folder. The project repository (<https://github.com/minhkhoo/motioncapture>) contains the firmware, the capture and processing software and their documentation. The hardware files, bench recordings, raw IMU files for the 81 recordings that have one, the quality-control table for all 139 recordings, the feature table for 135 recordings and a data dictionary are in the folder "Data and code" of the supplementary materials, together with the scripts that reproduce every number and figure in this paper, including the check of the samples around contact; the complete supplementary materials are archived at Zenodo (<https://doi.org/10.5281/zenodo.23540261>) under a CC BY 4.0 licence. In the released files the amateur players carry the codes P6 to P12, which correspond to A1 to A7 in this paper in the same order (Supplementary Table S4). Raw video is not shared because participants are identifiable.

Conflicts of interest. T.H. is the founder of Two Sigma Lab, the education company that mentored and funded this student project. The authors declare no other competing interests.

Use of AI tools. We wrote this paper with the help of AI assistants. An AI assistant (Claude, Anthropic) was used under the authors' direction to help us draft and revise the manuscript text, to write and check the data-analysis and figure scripts, and for language editing and formatting. Earlier versions of the manuscript were also reviewed by AI agents acting as independent reviewers, alongside internal review by the authors. The study design, the experiments, the data, the interpretation and the conclusions are our own. We checked and revised all AI-assisted text, code and results, verified every cited source, and take full responsibility for the content.

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Tables

Table 1. Bill of materials for one wrist unit (retail prices, Vietnam, May and June 2026). Suppliers and part numbers are in Supplementary File S1. Prices are rounded to the cent; totals come from unrounded prices.

Component	Qty	Cost (USD)	Function
Arduino Nano 33 BLE (original, LSM9DS1 IMU)	1	34.54	Microcontroller, Bluetooth radio and IMU
MH-CD42 module (upgraded variant)	1	1.17	Charges and protects the cell; 5 V boost
Lithium polymer cell, 3.7 V 200 mAh	1	1.30	Power
USB-C input board	1	0.35	Charging input
Velcro strap	2	2.19	Attachment
Slide switch	1	0.03	Power switch
3D-printed PETG case	1	0.38	Enclosure
28 AWG wire and JST connector	0.3 m	0.06	Connections
Total		40.02	

Table 2. Quality-control checks, applied in order. The check of the samples around ball contact described in Section 2.5 was applied after the fact and is recommended as an additional step for the wrist sensor.

Channel	Check	Threshold
Camera	Video present	file exists
Camera	Skeleton tracks the hitter	visual confirmation through the spike
Camera	Frame timing	at least 25 frames per second; largest gap at most 100 ms
Wrist sensor	File present	data file written
Wrist sensor	Throughput	at least 30 Hz; packet loss at most 50 percent of the 100 Hz design rate
Wrist sensor	Motion present	peak acceleration at least 2 g and peak angular velocity at least 100 degrees per second

Table 3. Bench test of one wrist unit at rest. Gyroscope values are in the library scaling described in Section 2.5.

Measure	Result
Acceleration magnitude, six orientations	0.910 to 1.076 g
Mean absolute error from 1 g	44.8 mg (4.5 percent)
Maximum absolute error from 1 g	90.1 mg (9.0 percent)
Gyroscope bias (x, y, z)	-7.4, -1.0, -2.3 degrees per second
Gyroscope drift after bias removal	16.1 degrees per minute

Supplementary material

All supplementary files are available in the supplementary materials folder and are archived at Zenodo (<https://doi.org/10.5281/zenodo.23540261>).

- **Supplementary File S1. Build guide.** Parts and suppliers, wiring and power path, enclosure, assembly steps and safety, firmware and data format, capture software, bench procedure, field procedure, synchronisation, pose-estimation settings, quality-control and feature definitions, and design changes made during the study.
- **Supplementary Table S2.** Price points and sources for commercial motion capture systems.
- **Supplementary Table S3.** Wrist sensor outcomes and accelerometer settings by session.
- **Supplementary Table S4.** Per-player summary of sessions, recordings and outcomes, with the player codes used in the released files.
- **Supplementary Figure S2.** Wiring and layout of the wrist unit (in Supplementary File S1, Section S1.2).
- **Supplementary Data and Code.** The folder "Data and code": hardware files, bench recordings, raw IMU files (81 recordings), quality-control table (139 recordings), camera feature table (135 recordings, eight features), data dictionary and scripts, as listed under Data, code and hardware availability.