

Context awareness for health and fitness : a case study

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ABSTRACT

Systems that can provide metrics on overall quality of closed, cyclical sports technique across different athletes can assure them how well they are minimising their risk of injury and optimising the effects of their training.

The design, implementation and evaluation of a portable and inexpensive system is presented to augment exercise equipment in gyms or the home with synchronised multimodal sensors. It automatically provides basic, real-time and post-workout technical feedback when expert coaches are unavailable; intra-cycle events are used to calculate performance metrics.

Indoor rowing is used as an example application domain given its popularity, technical complexity and constrained capture requirements. The system is evaluated through the data and observations collected during deployment in an active boathouse for over a year and its accuracy at discriminating 16 trained and novice athletes.

Keywords

application of ubiquitous portable sensors, HCI, qualitative multimodal real-world activity recognition, feature extraction, skill assessment, health, sports

1. INTRODUCTION

Automated understanding of human motion is possible through machine assignment of hierarchical levels of meaning to significant segments of time series of performance kinetics. Anatomical, temporal and potentially probabilistic models of human motion allow classification, regression analysis, comparison and description of how people are moving. Applications for human motion capture and analysis exist in intelligent monitoring of anomalous or particular behaviours, animation and augmented reality in domains including health, surgical procedures, rehabilitation, gait analysis, physiotherapy, fitness and exercise, manual labour, sports training, security and control interfaces.

Work within specific domains brings the potential for customised algorithms and better results. Historically, rather fringe actions and activities have been classified [4]. Little work even in affective computing exists in qualitative analysis or specific tasks [12], especially recognising subtle variations in the same sporting gesture.

Mobile systems have been characterised by their wireless capabilities rather than the ubiquitous nature of sensors and there have been a limited number of modalities in multimedia systems. This work considers ambient intelligence from portable, autonomous systems that usefully interpret human motion captured by ubiquitous, multimodal sensors.

Both vision systems [2] and wearable sensors [19] are used. Higher dimensional vision-based features allow more sophisticated models but their sensor infrastructure prohibits monitoring to localised spaces and shorter-term performances. Although recognition algorithms can directly use discriminative features, potential lies in methods from template matching, though neural networks and probabilistic graphical models to linear dynamical systems.

Rowing can be physically demanding and using an ergometer is common practise in cardiovascular exercise. Automated feedback from such systems that can recognise poor technique would help to enforce safety as using inappropriate movements can cause injuries [20]. It would be objective and unfaltering, unlike expensive human coaches, simultaneously measuring many aspects of a performance with higher fidelity than humans. Automated systems strive for sophisticated interpersonal communication that matches the effectiveness of human coaches.

This paper presents a novel system to be deployed in both elite training facilities and recreational exercise environments and implemented for an indoor rowing ergometer. The main contributions are: (1) A comprehensive review of motion capture systems for rowing. (2) Demonstrating how state of the art Ubicomp sensors can form a functioning system that can quickly capture large amounts of high fidelity, multimodal performance kinetics. The choice, positioning and synchronisation between multiple sensors of different types are addressed in capturing how users coordinate their movements relative to the equipment. Calibration, data segmentation, reliability, power, privacy issues and deployment methodology trade-offs are addressed. (3) A system that allows novel and useful real-time and post-session feedback.

(4) Automatically measuring overall performance quality and identifying undesirable technique is shown to be possible to an accuracy of 84.5% by highlighting a significant, measurable distinction between trained and untrained athletes. Experiences of long-term deployment in a real world environment are discussed. (6) The system allows characterisation of new sensor signals with respect to performance quality. (7) Potential datasets aid gesture recognition of useful, complex coach-defined feedback.

2. AUTOMATED FEEDBACK CHECKLIST

Challenges stem from deployment environments and use of data for characterisation, evaluation of recognition algorithms and as basic, real-time and post-workout feedback. Realistic and uncontrived performances from rowers within a familiar environment are required. The stylistic, qualitative and anthropomorphic variation in the complex technique of rowing means a large corpus is required to represent a significant population. Indexed, segmented data allows review of performances, encouraging use.

To collect enough authentic data the system must be portable and quickly augment equipment in real, training and fitness environments. Compatibility across different equipment maximises deployment flexibility. For unsupervised use it must be autonomous and require minimal maintenance and no manual organisation of the dataset once deployed. The system must be robust enough to leave unattended in a busy and hazardous gym or boathouse.

Discomfort is undesirable, impeding capturing a maximum number of natural performances. An athlete can not be expected to reliably place wearable sensors on deformable skin. Sensor signals must be synchronised and aligned to a familiar co-ordinate system to be easily, manually compared. In recording personal movements privacy must be respected.

To fully investigate the domain sensible numbers and modalities of inexpensive, high fidelity sensor signals including 3D position, force and image time series should be available from sensors placed freely in potentially useful positions to best represent the particular performance. Preliminary experiments [8] show interesting body movements of several m/s and a few millimetres.

3. RELATED SYSTEMS

Generic sensors [16, 14, 12, 10, 17, 5] lack autonomy, real-time feedback, data logging, the ability to annotate data or can't be customised. Others systems only use single modalities [15, 4, 3].

Potentiometers only measure 1D position with error up to 4cm during rowing [17]. Measuring force applied to the handle and foot stretcher of a rowing ergometer is common [5] but tends to use bulky force plates. Rowing simulators [7, 24] are autonomous but not portable, give seat position from an infra-red position sensor [7] or potentiometers [24] in different coordinate systems to handle motion and synchronisation is not mentioned. Orientation of oars [7] may not be as familiar as position and no accuracy is quoted.

Markerless motion capture often has low frame rates and using 2D images requires image processing to track unsta-

ble features in variable lighting conditions with infrequently revealed background due to hierarchical, articulated movement. Probabilistic 3D reconstruction [18] models parametric, kinematic chains with image descriptors; accuracy of cms is conditioned by expensive priors. Robustness is achieved with infra-red depth cameras; Microsoft Kinect has shown a pronounced non-linearity between precision and depth: 1.3mm at 60cm and 6cm at 5m. Other 3D model reconstructions [13] require constrained lighting conditions. Marker-based optical motion capture systems [1] used in [14, 8] allow sub-millimetre accuracy at over 200Hz but require much infrastructure, are fragile and expensive. Of comparable accuracy and sample rate but for a lower cost and infrastructure, commodity infra-red cameras can be used [11, 22], but experiences of practical implementations including camera positions, capture volume, reliability of correspondence and synchronisation are required.

FSR technology for obtaining data at a high frequency from a highly robust and flexible sensor placed in shoes by [15] gives foot contact times to a few ms. A greater number of different sensors are used in [23] and validated over 20km, giving helpful contact times. Drift in inertial measurement units accurate enough for pedestrian localisation are not suitable for unknown body movements [16]. In [7] Nintendo Wii remotes measure the rotation of oars.

Single cameras are used to recognise large-scale gestures [21]. Accelerometers give unfamiliar signals but are used for recognising quite differing activities including sports [12, 9] including rowing using joint angles [6] with little success. The most similar work [14] successfully, automatically grades karate performances.

4. MOTION CAPTURE CONTRIBUTIONS

1. A complete and self-contained whilst modular and portable system that tracks familiar 3D spatial positions of sports equipment rather than inertial measurements, without being worn by athletes.
2. Measurement of both force applied to equipment and its spatial positions, corresponding to multiple body parts, within the same coordinate system, to mm and ms accuracy. Within rowing systems, the handle and seat have not been placed within the same coordinate system.
3. Capture of synchronised sensor data over multiple modalities including conventional video for real-time feedback and post-session analysis. This includes aligning to a familiar coordinate system.
4. A practical implementation of an optical motion capture system based on inexpensive, lightweight, commodity hardware that achieves sufficient coverage for high fidelity position tracking of enough markers.
5. Evaluation of FSR technology in rowing for measuring magnitude and timing of forces.
6. Provision for annotation of the data captured.

5. SYSTEM DESCRIPTION

As illustrated in figures 1 and 2 a wide angle 30Hz video camera, a 3D optical motion capture system tracking up to 4 infra-red LEDs, a number of pressure sensors as used in [15] and a proprietary device to measure the force applied to the rowing machine handle at 20Hz are synchronised using a single clock. Four position markers are managable and useful allowing tracking of a free point within a coordinate system defined by 3 others points. Although easily occluded, flexibility exists in placing the battery powered, lightweight, wireless cameras. Markers can be worn if necessary but augmenting equipment has few disadvantages. Cyclical closed sports may not require tracking of the whole body; biomechanics literature and other work [8] identify 3D position of the handle and seat important in rowing technique. One marker is attached to the handle, two to the seat and one to the rowing machine. The single axis and 25cm² surface of the FSRs allow them to offer an additional perspective on the performance and force applied though the ball of each foot used in coaching and measured. Their sensor node allows for wired and wireless data transmission for portability.

Correspondence and identification of each infra-red (IR) marker is achieved through known geometry of calibration markers and template matching during rowing. As closed sports and exercises are often cyclical and such few sensors are used, some of which will be stationary, it is often possible to predict markers position to non-overlapping areas of the image, given the flexibility in placement of markers and cameras. This is shown for one camera in figure 3. Equipment can be stabilised against vibrations from zealous use.

The most recent IR camera frames are paired to triangulate 3D position. All FSRs are simultaneously read by the sensor node. Any drift in the video camera clock is reset with the system every 24 hours. An application specific world coordinate system chosen to allow natural comparison with the mental model of the user is relative to and aligned with the main axes of the ergometer and can be updated during system setup, after every complete performance segment or post-session. Principle component analysis and the position of the 2 seat LEDs over time allows an X-Z plane and Y axis to be calculated; the third LED defines the origin. Using openCV, calibration gives the intrinsic and distortion parameters of the fish-eye lens and intrinsic, distortion and extrinsic parameters of the IR cameras as well as the correspondence template and application coordinate system.

Custom, motion activated, IR LED units conserve battery power. The FSR iMote2 sensor node is powered over USB, with a backup battery. The rowing machine performance monitor uses batteries. The IR cameras can be battery powered for portability but inserts provide a rectified 3V permanent supply, also used to power a relay controlled over a serial port and used to hardwire otherwise manual pairing of the Bluetooth IR cameras during system initiation.

The data streams of accumulated samples from all sensors are segmented by thresholding extremities of the handle motion. Rather than encoding video in real-time, the camera is periodically turned on/off and raw video frames are stored. Raw kinetics are displayed as real-time feedback.

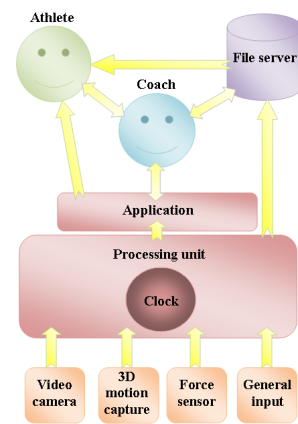


Figure 1: Schematic of the complete system including flow of information

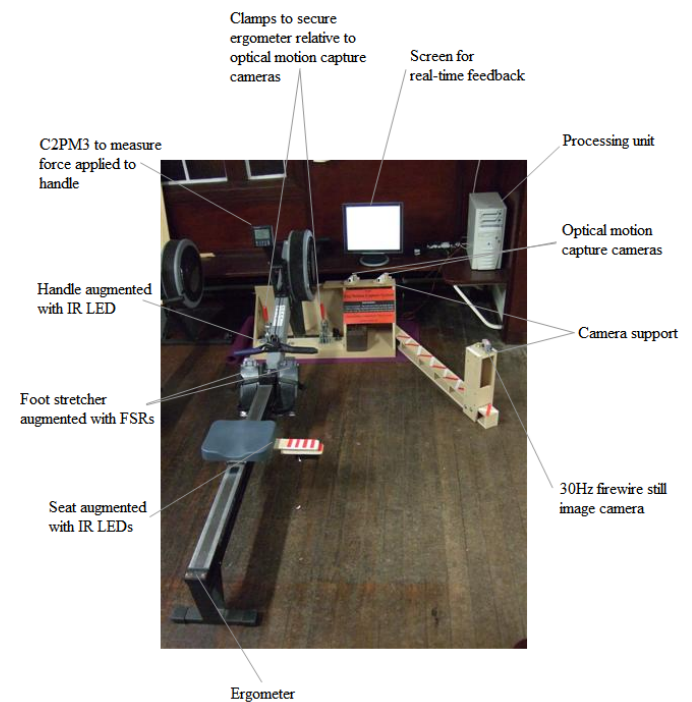


Figure 2: System deployed in a university boathouse

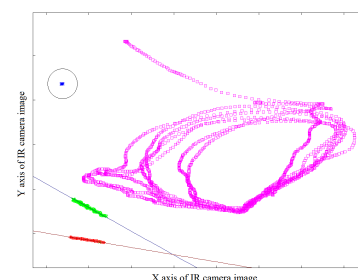


Figure 3: LED positions for an IR camera during rowing, with template used to identify markers for correspondence. Purple - handle; red and green - seat LEDs, blue - origin LED

6. SYSTEM EVALUATION

6.1 Functionality

Calibration of the system takes less than 5 minutes and need 20 different views of the IR calibration rig.

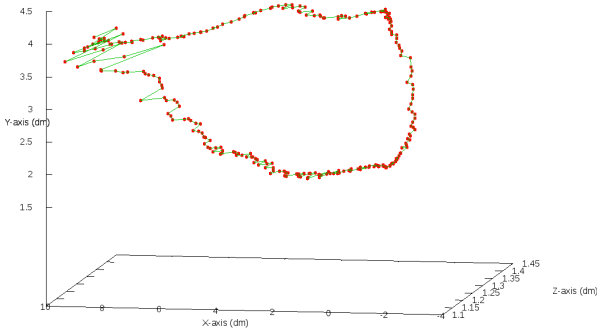


Figure 4: Handle trajectory in world coordinates

Precision of the optical capture system is shown in figure 4; the speed is not constant; as the IR marker moves beyond approximately 150cm from the cameras precision degrades due to low camera resolution, small baseline and marker battery level. A video frame from post-session feedback (figure 5) illustrates success deploying the system and forms of real-time feedback generated. Visual inspection confirmed expected functionality, negligible synchronisation error and low sample rate for proprietary measurement of handle force.

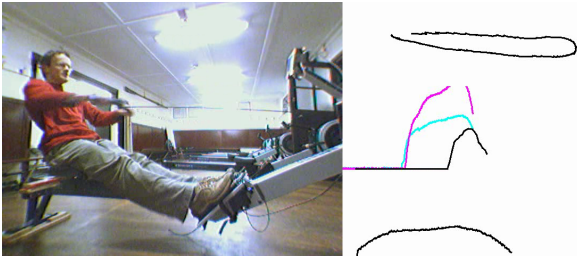


Figure 5: Image from a post-workout feedback video. Camera footage (left) is synchronised with kinetic data: a side profile of the ergometer handle motion (top right), force profiles (middle right) of feet (cyan, magenta) and handle (black) and a derived measurement: the horizontal distance between ergometer handle and seat (bottom right).

6.2 Measurement of overall technical quality

One dimensional metrics designed to assess overall quality of technique are evaluated by classifying good and bad performances from two populations: 8 novices not instructed in rowing but may go to the gym and 8 amateur rowers undergoing training. Such disparate groups justify assuming any amateur performance is better than any novice one.

Basic rowing was demonstrated to novices by amateurs and their questions answered. Further teaching could confuse and performances may not indicate the general population's ability. Novices were instructed to row at a comfortable rate to feel they had a work-out; some maintained a speed estimated by the ergometer monitor. Amateur performances

Table 1: Population statistics

Number of novice performances	224
Number of amateur performances	183
Base line classification accuracy (%)	55.0

Table 2: Classification accuracies (%) at 100Hz for both and single populations using different modalities and events including force applied to handle (handle_f), motion of handle (handle_m), and total force applied through both feet or the left foot.

Metric	Total	Novice	Amateur
Foot onset, handle_f peak	60.93	68.30	51.91
Start of seat motion	60.93	72.77	46.45
Foot release, handle_f peak	62.41	92.41	25.68
Handle_f peak	62.90	71.43	52.46
Handle_f & feet peaks	66.09	54.91	79.78
Handle_f & foot peaks	70.52	85.71	51.91
Performance duration	71.01	78.12	62.30
Handle_m peak	81.82	98.66	61.20
Handle_f & handle_m peaks	85.26	91.96	77.05

were from real training sessions. All performances lasted approximately 1 minute and included any sensor error.

6.2.1 Results

Use of the system for rowing suggests general features from performances of closed sports and exercise for designing metrics: Differences in peak, onset and offset events in sensor signals are normalised by performance duration detected by handle motion.

Table 2 lists the events used by metrics along with the classification accuracy. Total accuracy considers all performances and is computed by finding the threshold along the metric scale that most accurately splits the performances into good and bad quality. Specific populations uses the same assignment but just consider the respective performances. Each population size and therefore baseline accuracy are shown in table 1.

The relationship between sample rate and metric classification accuracies are shown in figure 6. The maximum sample rates for each sensor are different and linear interpolation is used to resample above and below their thresholds so each experiment uses one sample rate across all modalities. The metrics were repeatedly used with the following rates selected manually for informative results: 200, 100, 50, 20, 10, 5, 2 and 1Hz.

6.2.2 Discussion

It is possible to significantly improve over the classification baseline using metrics and this system; assuming distinct populations accuracy reaches 84.5%. The evenness rather than clustering observed in the spread of values suggests sensitive metrics. When using handle force and handle motion peaks 91.96% is achieved for just novices, 77.05% for just amateurs. I.e. a performance scored above the threshold is likely to be of amateur level. Two of the top three metrics involve more than one modality which suggests useful events exist across modalities and their combinations can

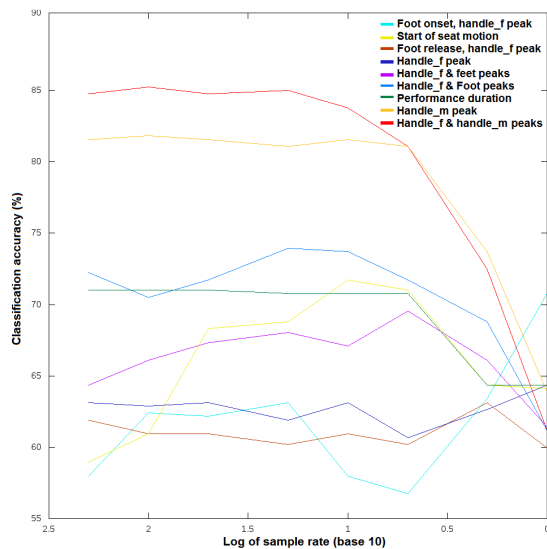


Figure 6: Sensitivity of metric classification accuracy to sensor sample rate

improve accuracy.

Most metric’s accuracy slightly decreases overall with sample rate above 10 to 5Hz and significantly decreases below. This is expected due to information loss. The metrics mostly maintain relatively accuracy for a given rate. The more accurate a metric at higher rates, the greater the reduction in accuracy with rate and most metrics achieve just above the baseline at 1Hz. The results show the difference between peaks in handle motion and force signals provide best classification above 5Hz and the handle motion peak event allows slightly better results below 5Hz, both normalised over the performance duration.

Stroke duration achieves 71% but performance execution time is not indicative of skill with correlation coincidental: novices may be cautious and slow or naive and rush. Accuracy using the start of seat motion abnormally increases as rate decreases. This is because as sample period increases the movement detection threshold becomes too sensitive and is immediately exceeded causing the metric to tend to stroke duration as illustrated in figure 6.

The time between peak handle and peak feet force and between peak handle motion and force are interesting to coaches. Perceived wisdom suggests both are correlated with expertise; results for both metrics are above the baseline but support the latter more.

State of the art rowing ergometers give limited feedback using handle force; magnitudes are anthropomorphically variant. They can detect strokes’ start, end and peak handle motion events but accuracies are unreported and affected by a slack chain or moving the handle by pivoting. Using the relative time of handle force peak over stroke duration achieves only 63.1%. If the proprietary systems can detect motion events synchronised with handle force as accurately as optical systems, this paper shows a maximum accuracy of 85.01% could be achieved at commodity rates of 20Hz using

a multimodal metric. Tank rowing would benefit from this paper’s system as no handle chain exists and 20Hz may not be sufficient for finer grain classification.

Favourable results are achieved by this first study of automated, qualitative assessment of rowers using cross modality events. Current ergometers data has sufficient rate for coarse grain classification. The system provides richer datasets for metrics sensitive to other technical aspects. Results are generalisable to other sports by the applicability and existence of similar sensors and events.

6.3 Experiences deploying the system

Infra-red interference is problematic for the optical system. Sources of flooding or reflected light were found to include sunlight, incandescent lights, other IR LEDs, retro-reflective safety material and reflective metal. Users occasionally occluded the LEDs of the ergometer handle by hand or twisting, even though the LED emission angle is high. Weighting down and a non-slip mat between the wooden system and floor were necessary to not require regular recalibration. The FSR measurements of force magnitude drifted to several orders of magnitude of difference after 12 months.

The system was robust and reliable when appropriately positioned, requiring minimal maintenance such as charging the batteries and occasionally rebooting. One IR LED unit failed once in 1 year. Although the system was less portable than an erg, its portability proved useful when moving it between a laboratory, boathouse and other demonstrations.

6.4 Lessons in capturing exercise

During coaching the handle motion was used occasionally and the derived measurement was particularly useful. Coaches were interested in the shape and timings of the handle force and interested but unfamiliar with foot forces. They began to characterise such unfamiliar novel kinetics.

A balance must be needed between ‘*Fade into background*’ and ‘*Inform and encourage*’. The latter was chosen as recording videos raises privacy concerns. The interface was seen to engage the athletes and on-line post-session feedback was used by some however most sessions recorded were relatively short suggesting the users were only interested in using the system for technical sessions, not cardiovascular training. To maximise reputation, before deploying the system it is important to minimise development in situ: measure the space available, ensure lack of reflective materials, sample the friction between the floor and system and ensure use of the augmented ergometer isn’t impeded.

Some athletes were observed to be highly particular over which piece of equipment they use and finding any augmentation off-putting and disruptive to their routine although equally others were able to ignore it if they wished and found the system and feedback helpful. The system has a short but steep learning curve and demonstration is very important to encourage use, if not logistically easy. The physical size of the camera support necessary to obtain the correct viewing angle meant the system was set away from other ergometers discouraging comradery. Rowers were uncomfortable with being videoed and a privacy screen was added but needed to be automatically turned off as was often left up.

7. CONCLUSION

Insights have been gained into investigating intelligent monitoring to automatically provide awareness of the health, fitness and skill of patients and athletes within their natural exercising environments. The system can provide useful datasets and feedback and is well suited to measuring kinaesthetic performance events beyond state of the art systems that are useful landmarks for effectively symbolising performance quality.

The implementation for rowing illustrates important development challenges and shows sports engineering requires highly customised systems specific to individual sports and exercises before further research contributions can be made as each domain has very different equipment, constraints and optimum sensor choice and placement. The flexibility of this system goes some way in addressing this problem.

8. FURTHER WORK

The iMote2 supports 2 more FSRs which could be placed on the seat and may help to locate the shoulder and head. Additional sensors, live video and 3D visualisations could improve the possible datasets. It would be interesting to investigate the utility of different forms of feedback and their effects on performance through collection and annotation of a dataset to evaluate more algorithms for further analysing performances.

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