Integral Kinesiology Feedback for Weight and Resistance Training

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***Abstract*—Existing physical fitness systems are often based on kinesiology. Recently *Integral Kinesiology* has been proposed, which is the *integral kinematics* of body movement. In this paper, we apply integral kinesiology to the bench press, commonly used in weight and resistance training. We show that an integral kinesiology feedback system decreases error and increases time spent lifting in the user. We also developed proofs of concept in aerobic training, to create a social physical activity experience. We propose that sharing real time integral kinematic measures between users enhances the integrity and maintenance of resistance or aerobic training.**

I. Introduction

This paper presents the application of integral kinesiology to weight training, resistance training, and the like.

The word "kinesiology" derives from the Greek words "$\kappa\iota\nu\eta\sigma\eta$" ("kinisi"), meaning "movement", and "λογος" ("logos"), meaning "reason", "explanation", or "discourse" (i.e. "study").

Kinesiology, is movement science, closely connected with kinematics. Kinematics, is the study of the mechanics of the motion of objects without considering the forces acting on the objects, i.e. typically the pure study of distance (or displacement) and its time-derivatives, speed (or velocity), acceleration, jerk, jounce, etc.

Integral kinematics [1], [2], [3] is kinematics in which we also consider the time-integrals of position, such as, absement [1], [4] (the first time-integral of position).

Integral kinesiology is movement science that includes position and its derivatives *as well as* its integrals. Integral kinesiology includes measuring the absement (time-integral of distance or time-integral of displacement) during exercise. We proffer as state-variables of a phase space, momentement (time-integral of momentum) and absement, upon which we may apply machine learning. The first machine learning algorithm to be applied to phase space was LEM, also known as the adaptive chirplet transform[5].

The word "integral" derives from the same Latin language root as the word "integrity", and "integer", meaning "wholeness" or "completeness", and this is apt, as integral kinesiology pertains to a certain kind of integrity through completeness (i.e. including not just derivatives of position, but also integrals of position).

The goal of this work is to develop a closed loop feedback system to improve the integrity of exercise training. Improvement of integrity means improvement in exercise form. Additionally, a system can helpfully alter behaviour in the long term, so that the user can adapt their behaviour to the

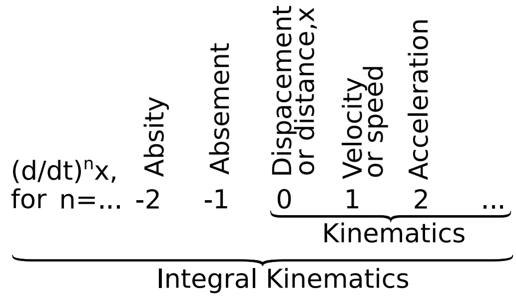

Fig. 1. Kinematics ordinarily involves the study of distance or displacement, x, and its derivatives, $\frac{d^n}{dt}x, \forall n \geq 0$. This gives us only half the picture. We wish to also consider negative n, i.e. integrals (integral kinesiology), such as absement $\int x(t)dt = (d/dt)^{-1}x(t)$.

feedback[6], [7], and thus optimize exercise even without the use of the system[8]. We have also proposed pro-social uses of this tool pertaining to sharing feedback amongst users to facilitate initiation and maintenance of physical activity. Therefore, our tools could greatly add to the amplification and maintenance of regular physical activity providing closed loop feedback in addition to social support (as suggested in [9], [8])

A. Background

Taking the derivative of a quantity is akin to acting on it with a *differential operator*, i.e. $(d/dt)^n$, where n gives us the nth derivative. For velocity we have $n = 1$, for acceleration, $n = 2$, for jerk, $n = 3$, for jounce, $n = 4$, and so on....

But this is only half the picture, i.e. we should also consider negative values of n for the complete picture.

When $n = -1$, the result is a measurement known as absement. Absement is the time integral of displacement or distance, and thus can be used to measure total deviance (error) from a baseline value that we wish to maintain. In weight training, one baseline we wish to maintain is the pitch of the barbell, which needs to stay level with the floor. Another dimension we want to maintain for proper lifting is the yaw, to keep the barbell steady from wrist rotations. In the current study, we offered only one form of feedback on the absement of pitch, while also simultaneously measuring the ongoing absement in the yaw. Therefore, the measurement of error that is of interest in the current study is the pitch absement. See Fig. 1 We assume small deviation, so that $\sin\theta \approx \theta$ for small θ, so absement can be approximated by anglement.

B. Related Work

Exercise has traditionally used metrics like distance, speed, and acceleration (for example see[10], [11]). Now, with in-

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tegral kinesiology, absement is a vital metric to consider when assessing the integrity of a lift during weight training. There are many existing ways to track motion, see, for example[8][12], [13]. We track motion and provide real-time feedback to users, such that they can correct their behaviors, as suggested in[7], in much the same way that bio-feedback has been previously used for rehabilitation[14]. Integral kinesiology can help with form during weight training, by providing feedback to the lifter about their absement, as deviation from maintaining proper form. As the absement in prescribed movement grows, the user can be provided a cue that creates an incentive toward proper form (or a disincentive away from bad form). This cue takes the form of an indicator that directly represents the current error.

In past works, integral kinesiology has been applied to the training of core muscles using fitness games[2]. The MannFit mobile app[3] was previously developed to give feedback about absement to motivate a subject in a planking task, where growth of the absement produced audio or visual feedback such as warping of accompanying music, or simulation of spilled water[2]. Users of the MannFit app experienced greatly decreased absement during planking, suggesting a more stable plank form. Also, training with this feedback system allowed for the development of longer, sustained, low-absement planking sessions. We focused on monitoring absement during barbell bench presses, to measure the error of the user whilst also updating the user on their error through real time visual feedback built into the bench press rack (see Fig.2). The time integral of distance is the total error in deviation from zero (straight), in position, during weight training. We use absement as a measure of error across various axes. Here, the tilt of the bar (the pitch, see Fig. 3) during lifting is measured and relayed back to the user with visual feedback in real time. Overall, the system presented here is an application of the principles used in the previous MannFit mobile app[2]. The mobile portion of the new system presented here (Fig. 4, 5, 6) is implemented as an extension to the already existent MannFit application[2].

II. Integral Kinesiology Rationale in Weight Training

Integral kinesiology involves a combination of strength and dexterity, and puts emphasis on simultaneously maintaining and training strength and fine motor control. During weight training, individuals must engage in proper lifting form to avoid injuries, ensure the proper muscles are worked, and maintain muscular symmetry of the body [15], [16]. A common problem for individuals who weight train with a barbell is improper form in the yaw (maintaining the forces in the rotation of the barbell), in the speed of the lift movement, and in the pitch (maintaining the forces on the tilt of the barbell). This is an issue at all levels of experience, but is especially true for novice lifters[17]. Currently there is no quantitative way to effectively measure bio-mechanical errors in performance on a bench press. Qualitative feedback from a personal trainer is helpful to the user in real time. However, access to personal trainers is limited, and an observer (no matter their training) simply cannot provide the speed and accuracy of instruction that a real-time electronic closed-loop feedback system can. Thus, integrated kinesiology applied to bench press can fill a major need, providing easier access to precise real-time feedback. Feedback helps individuals performing exercise[18]. In addition, the application presented here will also store absement over time, across repetitions, sets, and workouts, providing opportunities for long term review and assessment.

The bench press (see Fig.2) is one of the most common weight training techniques. It is a compound workout that primarily works the triceps brachii, pectoralis major, and the anterior deltoid. During a bench press, lifters often experience bad form (error) on multiple axes. One of the most common errors that occurs is an asymmetry in arm extension whilst performing the lift, causing an increase in absement in the pitch [18] . This results in the barbell becoming unparalleled with the floor, improper muscles being worked, and the creation of muscular asymmetries, all of which can result in injuries. Here, we can define error and infer asymmetry in muscle recruitment by assessment of how parallel the barbell is with the floor. Therefore, when users have a tilt in the bar, the system records the absement of the tilt and simultaneously provides real time visual feedback for the user to correct the tilt of the bar during the lift. By storing absement across workouts, the user is able to track these asymmetries over time.

III. Hypothesis

We hypothesize that providing a participant using a bench press with an absement-based feedback system of pitch (i.e. feedback based on the tilt of the bar), there will be an improvement in their overall form. A closed-loop feedback system, where the participant is a part of the loop, will result in lower absement and therefore better form. In addition, we take simultaneous measures of absement in the yaw (rotation of the barbell), while not offering feedback for it. We hypothesize that having feedback about the pitch will reduce the absement in pitch, but will be unlikely to improve (reduce) absement in yaw.

IV. Experimental setup

The experimental setup consists of five main components: an iron barbell, an MPU-6050 inertial measurement unit, a Sequential Wave Imprinting Machine (S.W.I.M.)[19] (implemented using a Teensy 3.2 microcontroller and an Adafruit DotStar APA102 SMD LEDs), an Espressif ESP32 microcontroller, and a user-facing mobile Android application. A system diagram is shown in Fig.4.

The system begins by having the MPU-6050 module mounted on the barbell to measure the acceleration and angular velocity along 3 axes (x, y, and z). Then, following the flowcharts shown in Fig.5, the ESP32 microcontroller begins by initializing the home position and resetting the LEDs on the S.W.I.M. It also initializes the Bluetooth interface for connectivity to mobile devices. The ESP32 then reads acceleration and angular velocity and processes it to determine

Fig. 2. A user of our integral kinesiology system performing a bench press. A SWIM [19] (Sequential Wave Imprinting Machine) is used to guide the user through the exercise by way of real-time visual feedback on form. Note the rope which provides dissipative friction (energy loss) to dampen the inertia of the weights. It is also connected to a spring, so that all 3 forms of impedance are present.

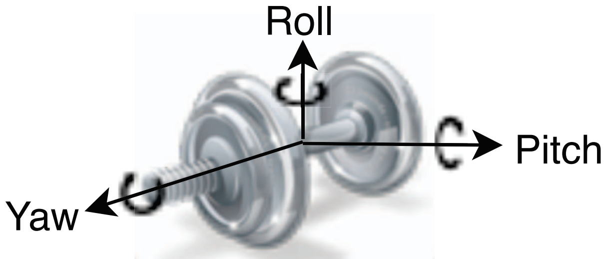

Fig. 3. Roll, yaw, and pitch with respect to the barbell

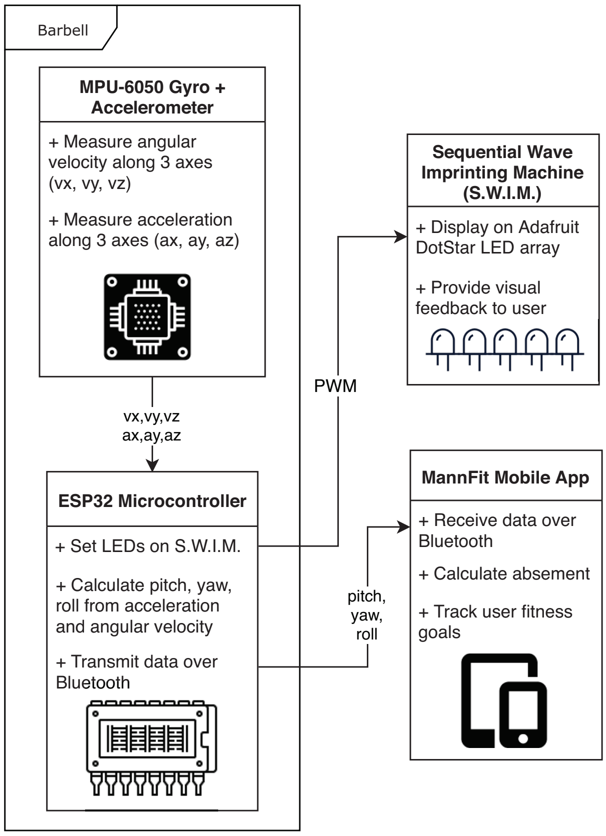

Fig. 4. System Diagram of Experimental Setup

pitch, yaw, and roll of the barbell relative to its home position. Roll is defined as the rotation of the barbell about the axis orthogonal to the ground. Yaw refers to the rotation of the barbell about the axis projected along the length of the bar bell. Pitch is rotation of the barbell about the last axis (See Fig. 3). The ESP32 uses the pitch data to determine where to position the displacement indicator light and the colour of every pixel on the S.W.I.M. The S.W.I.M. is mounted on the bench press rack at a location directly above the user's head, in line with the participant's line-of-sight whilst performing the exercise. The purpose of the S.W.I.M. is to provide visual feedback to the user while they are exercising. The S.W.I.M. displays an intuitive blue LED indicator that moves along the S.W.I.M. in tandem with the tilt of the bar, where a tilt (and thus form error) to the left moves the LED indicator to the left, and a tilt to the right moves the LED right. A static white LED is lit in the middle of the S.W.I.M. as a reference for the center. Users are informed that the blue light provides feedback about error in barbell tilt. Users are instructed to keep the blue light as close to the center light as possible. The user therefore is part of a closed loop feedback system where they are able to correct for error by aligning the moving blue LED with the white LED that marks the center. For the purpose of demonstration, Fig. 2 shows a similar setup but with the S.W.I.M. mounted directly on the barbell. This is used for capturing long exposure photographs to visualize absement. (S.W.I.M. lighting algorithms were modified in this example for visual effect).

Finally, the ESP32 also transmits data regarding the experimental setup, pitch, yaw, and roll over Bluetooth to the user-facing MannFit mobile application, shown in Fig. 6. The MannFit mobile application handles data collection for this experiment by logging the participant, trial number, number of reps, weight on the bar, and providing controls for the setup of the experimental system. Within the app, the pitch and yaw values are integrated over time to determine the user's absement. This absement data is displayed on the screen and also logged on the user's phone. All data is stored locally on the mobile device in the form of CSV files. The app also allows the user to view their absement across multiple exercises and see how their fitness and form improves over time.

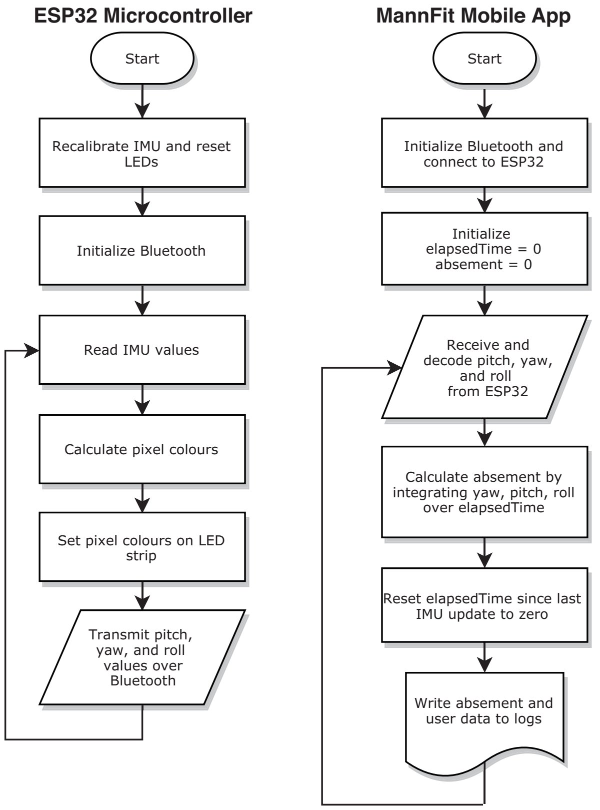

Fig. 5. Flowchart of ESP32 Microcontroller and MannFit Mobile App

Fig. 6. MannFit Mobile app which handles data collection and records absement.

V. Experiment

Participants (n=6; n=2 female) were asked to perform four sets of five reps on the bench press. For two of these sets, the participant received no visual feedback. For the other two sets, each participant performed the bench press with visual feedback on. The order alternated in which the participants performed with or without a feedback system and the alternation in trials was counterbalanced and randomized across subjects. The weight that the participants used was self-selected but stayed consistent across repetitions within subject. All subjects were instructed to pace their movements to a time interval of three seconds on the down-movement, and three seconds on the up-movement. The time for each lift session was recorded and the absement was normalized to the overall time for each lift session (absement/time). Measures of absement in pitch and yaw were recorded for each of the four lift sessions independently, and compared across conditions and between subjects. Therefore the absement measures reported are absement/time, rather than raw absement measures. Within each participant, absement data from both sets without feedback were averaged and compared to the data collected from both sets with feedback.

We compared absement between every session in which participants had feedback compared to every session without feedback. Comparisons in absement between feedback on vs feedback off sessions were made using unpaired t-tests. This data is shown as the first graph in each of the three results figures (see Figs.7, 8, 9 A).

Because the participants in this study varied from novice to regular bench press users we wanted to also compare the general effect of visual feedback on absement and time to complete the set within each participant. For this we used paired t-tests. This data is shown in the second graph in each of the 3 results figures (see Figs.7, 8, 9 B).

One-way repeated measures ANOVA were used to assess if there was a change over the four lifting sets in overall time, absement in pitch, and absement in yaw. This data is shown in the third graph in each of the 3 results figures (see Figs.7, 8, 9 C).

VI. Results and Discussion

An unexpected and interesting observation was seen in the increase in time taken to complete five reps when feedback was provided. Despite all participants being instructed to pace their lifting (three seconds on the down-movement, and three seconds on the up-movement), we found that when comparing the amount of time to complete the sets with feedback on vs off, feedback significantly increased the time to complete the lift set ($t_{22}=2.5$, $p=0.01$) (see Fig.7). This effect was further replicated within subjects, as when averaging the time taken to complete feedback on vs feedback off sessions, feedback off sessions were significantly faster to complete than feedback on sessions ($t_5=3.8$, $p=0.01$). Considering the time to set completion without the feedback system, participants completed their five reps significantly faster compared to when the visual feedback system was engaged across sessions ($F(5,15)=7$; $p=0.03$).

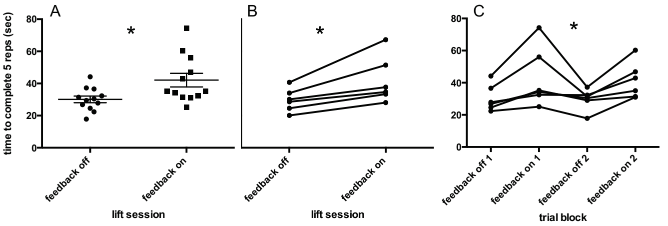

Fig. 7. **Time to complete 5 repetitions.** A) Each dot on the plot represents the total time to complete the 5 repetitions over a lift session in the feedback on or feedback off conditions. B) Within subjects having the feedback on increased the total time to complete the lift session. Each line and connected dots represent a single subject's average of the feedback on or feedback off sets. C) Across the four lift sessions each time the feedback was on, most participants had longer lift times when feedback was on vs. off, having more lift sessions did not speed up subsequent lift sessions if feedback was on. Each line and connected dots represent a single subject's measurements for each of the 4 sets*=p<0.05

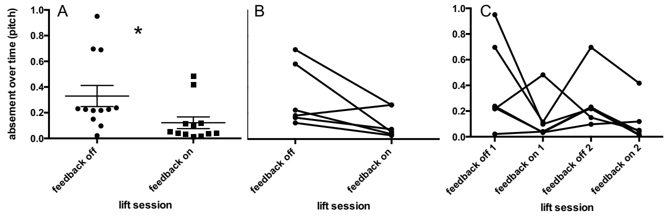

Fig. 8. **Absement in pitch over time.** A) each dot on the plot represents the total absement in pitch over time over a lift session in the feedback on or feedback off conditions. B) Within subjects having the feedback on decreased the absement in pitch. Each line and connected dots represent a single subject's average of the feedback on or feedback off sets. C) Across the four lift sessions, each time the feedback was on, most participants decreased absement in pitch compared to when feedback was off. Each line and connected dots represent a single subject's measurements for each of the 4 sets. *=p<0.05

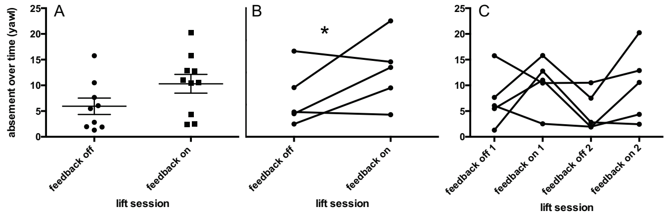

Fig. 9. **Absement in yaw.** A) each dot on the plot represents the total absement in yaw over time over a lift session in the feedback on or feedback off conditions. B) Within subjects having the feedback on increased the absement in yaw. Each line and connected dots represent a single subject's average of the feedback on or feedback off sets. C) Across the four lift sessions, each time the feedback was on, most participants increased absement in yaw compared to when feedback was off. Each line and connected dots represent a single subject's measurements for each of the 4 sets. *=p<0.05

We speculate that participants were taking more time to focus on the visual feedback and correct their movements when using the visual feedback system compared to having no visual feedback. Having no visual feedback may allow participants to focus on doing the reps within the requested pace, while also being prone to error in their form. Anecdotally, participants did comment on the lights in the feedback system and the behaviour of these lights as capturing their attention.

This effect of longer time to complete repetitions whilst providing visual feedback may also confer benefits to the bench press exercise regime. Resistance training performed with a normal number of repetitions but an increase in time under tension has been shown to increase muscle recruitment while decreasing muscle fatigue [20]. Thus taken together, our current closed loop integrated kinesiology visual feedback system may also include unexpected improvements in muscle recruitment and endurance during the lift session.

Given the discrepancy in time duration between conditions, we wanted to control for the total errors made over time, and therefore divided the total absement by time taken to complete five reps. This creates a metric that gives us a measure of error relative to the total time under tension that the participant experienced.

Receiving feedback about the absement on pitch significantly improved the absement measures in sessions when feedback was on compared to when feedback was off ($t22=2.2$, $p=0.03$). When looking at changes in absement within subjects, there was one subject that did not show improvements when feedback was on vs when feedback was off, however, the rest of the subjects showed trends for within subject improvements in pitch absement when receiving feedback ($t5=2.2$, $p=0.07$). Across all 4 sets, absement did not seem to improve significantly over lift sessions ($F(5,15)=2$, $p=0.12$). However, there was a general trend that sets performed when feedback was off had increased pitch absement, which is otherwise suppressed when the feedback was on.

Also of interest was the performance measures in domains in which participants were not receiving feedback, the absement in yaw. Overall, across feedback on vs feedback off sets, absement in yaw tended to be higher in the feedback on sets ($t17=1.8$, $p=0.09$). When feedback sets were averaged and compared within subject, there was significant increases in yaw absement when feedback was on ($t4=3.15$, $p=0.03$). Across all 4 sets, there was not a decrease in the yaw absement ($F1,7=2.1$, $p=0.17$). That being said, it is clear, from visual inspection of Fig. 9 C, that absement in yaw tended to decrease across sessions in some users.

This experiment is a powerful proof of concept to show the potential of closed loop feedback systems during weight training. However, we also tell a cautionary tale, that receiving feedback on one type of error (the pitch) improves upon that domain but may overcompensate, causing other aspects of the lifting action to suffer, as we saw with the increase in absement in yaw when the user receives feedback about the pitch. That being said, it seems that this effect of feedback on pitch absement impaired yaw absement in only some users, anecdotally the novice users. In general, all users showed improvements in yaw absement during the third and fourth lift session, suggesting that feedback on pitch may allow for overall improvements in lift form, once the user habituates to the visual feedback interface. Therefore, including additional feedback during the lift session may be of use to optimize training of the user for best lifting form. However, in pilot test sessions that included simultaneous feedback on yaw and pitch absement, users found it difficult to correct and concentrate with multiple streams of information at once. So there may be some benefit to limiting the feedback to one integral kinematic axis at-a-time, while also simultaneously measuring other integral kinematic components to assess for areas of improvement. The current experimental setup and mobile app will allow for feedback of one or more axes, and this is something that a user can control from the app interface if they want to change the type or amount of feedback they are getting.

The data presented here was collected in one day. The truer potential of a feedback system is in its ability to train a user in good form with long lasting adaptable behavioural changes, as seen in[6]. This type of training requires time to develop muscle memory to perfect lifting form. Thus, a more comprehensive experiment will be conducted to show the ability of a feedback system to train a user in proper form, while providing interpretable feedback for multiple axes of absement (pitch, yaw, and roll). This new experiment will involve testing users over a period of a month, while the user has electromyographic recordings ongoing with the lift sessions, where half of the participants receive no feedback and the other half do receive feedback. Data will be collected daily to assess for changes in absement as a user trains with or without feedback. The longevity of the feedback effects will be explored. That is, if, after a month of training, the user experiences significantly decreased absement scores with the presence of a feedback system, we would like to assess if the reduction in absement is maintained when the user stops training with visual feedback. In addition, it would be of interest to note if receiving feedback has any effect on the tension, fatigue or exertion of the muscles during the lift, as would be hypothesized from our findings in combination with the findings that increased time under tension increases muscle recruitment and endurance [20].

VII. Going Further: Big Data and Collaborative Web-based Integral Kinesiology Through IoT

A. *Collective experience fitness systems*

Weight training is typically a solo endeavour (i.e. one person actually experiencing the lifting, at any given time, even though there is often a spotter or a "buddy system" involved). We consider now a more inclusive form of Integral Kinesiology based on intelligent machines working in tandem [21]. We know, for example, the amplification of benefits of physical activity when exercising collectively. For example, cross-country runners, often run side-by-side, matching pace, and often breathing rate, and in doing so form a partnership and build comradery, while gaining knowledge of others actions in tandem with self [22]. For example, we proffer here two exercise bicycles connected in such a way as to simulate tandem cycling, i.e. to simulate a collective experience of cycling together, even among two people who are separated geographically. These may be friends, or even complete strangers. In a first prototype, we electrically connected two machines together, (using a wired approach for the prototype), so that when one machine runs, it alleviates load on the other machine. We chose machines having a Lundell generator, so that they are easy to connect, and mounted binding posts on the machines so that they could be linked by banana cables or wires. Fig. 10 is a photograph showing two Lundell generators, one in a bicycle and the other hand-cranked, as an exploration of this concept.

Fig. 10. Exploring the interconnection between electric machines. Here are two Lundell machines, one in a stationary bicycle and the other hand-cranked. The hand-cranked machine features a rotary SWIM (Sequential Wave Imprinting Machine).

In the next prototype, we connected machines using a Lab Quest MINI analog-to digital-converter, current sensors, and temperature probes for system monitoring [1], and devised an adiabatic calorimeter to capture work (energy) performed into the heating of water (this was a first-step toward a rowing-based ergonometer to be described in what follows).

Another example used here is rowing. Rowing involves powerful yet fine motor control, requiring strength (power), stability, and control (dexterity). In this regard, rowing is an ideal example of a sport that fits well within the integral kinesiology framework. Rowing is a collaborative sport done outdoors "On The Water" (OTW). Unfortunately when rowers train indoors, on separate machines, there is less teamwork or physical connectedness. Fortunately, though, when indoors,

[1]Authors wishes to thank Dr. Lawrence of BSS for the use of the measurement equipment used in the calorimetry experiments.

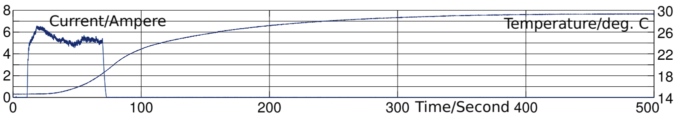

Fig. 11. Calibration procedure with known input to determine the temperature profile and system losses, time constants, etc., which the machine learning model adapts to.

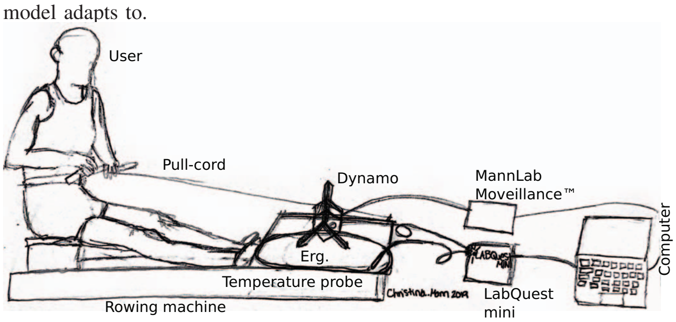

Fig. 12. Proposed instrumented rowing machine with a body of water in an adiabatic calorimeter for damping and sensing, a dynamo for group interaction, and a computer for IoT (Internet of Things) and web-based connectivity.

rowers may use use a water-based ergonometer. Ergonometry is itself an integrative measure, i.e. it integrates power (energy is the integral power). We propose a device and system that allows multiple rowers to row all at once, and thus removes the element of disconnectedness that we otherwise have in a gym setting. This can be done in small groups like two, or four, or eight rowers in one gym or in separate gyms across the globe. When OTW rowing, the water forms the "bridge" that unites the team members, i.e. they are connected hydraulically. Each oar affects the other oars, and here we propose to simulate this "water bridge".

We implemented an ergonometer within existing exercise machines and gym equipment by designing a water-based adiabatic calorimeter to capture and quantify energy generated by frictional (resistance) training. We calibrated the system with a known input (Fig 11), to establish the efficiency, losses, etc., using a simple machine learning model for the calibration profile.

This system is ideally suited to machines that already use fluid damping, such as fluid-based rowing machines. See Fig. 12 for a diagram showing system configuration. This form of hydraulic collaboration can also be done at larger scales, e.g. in the context of "Big Data", e.g. huge numbers of rowers around the world rowing at the same time . With millions of users tied into one system via IOT (see next section) we can capture large datasets for analysis [23][21].

B. Expansion via Internet of Things

In order to facilitate the generation and storage of vast amounts of data, the current MannFit system would need to be redesigned. At a high-level, the new design would follow a three-layer IoT architecture shown in Fig. 13 [24], [25]. The *perception layer* consists of the barbells, rowing machines, other sporting equipment and their attached sensors. The *network layer* is comprised of microcontrollers with integrated network cards, chip modems, etc. and computers/workstations connected to the sensors. These devices will then connect via

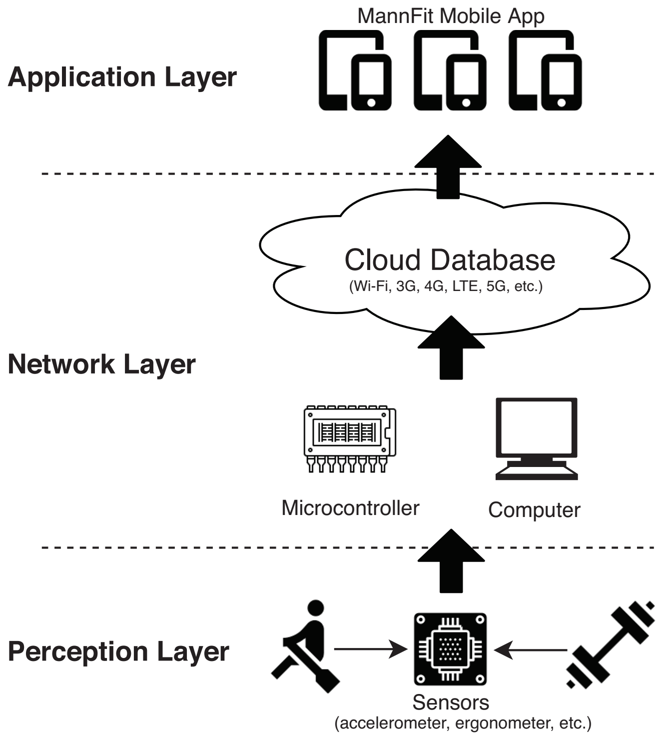

Fig. 13. Proposed three-layer IoT architecture of the future MannFit system.

Wi-Fi, 3G, 4G, LTE, 5G, etc. to a cloud database. All data will be stored in the cloud. Finally at the *application layer*, mobile devices running the MannFit mobile app will retrieve data from the cloud and provide fitness monitoring services to the user. We proffer to use the emerging Web of Things Testbed [26] to promote rapid development of the new MannFit system. This, as a whole, would effectively create an IoT sensing as-a service platform [27], where information about the sensory environment is provided to the user in a packaged service. This system would work as an IoT mesh network, with end-nodes (user exercise equipment) intercommunicating closely within gyms, cities, and the world (likely utilizing efficient IoT mesh techniques such as MQTT Middleware [28]) and classical client-server communications methods to sync with the cloud. A majority of the existing MannFit infrastructure can be reused in the proposed IoT architecture. The only major change would be replacing the existing Bluetooth interface on the ESP32 microcontroller with a network interface. Fortunately the ESP32 microcontroller already has the necessary hardware to facilitate both Bluetooth and Wi-Fi communications. Thus the required changes are purely software, allowing a cost-efficient improvement.

C. Inverses of Big Data and IoT

We proffer the concept of a "Securitree^{TM}" with 3 branches: (1) public safety; (2) security; (3) organizational efficiency, as we would often see in "health surveillance", but we proffer also roots of the tree for "health sousveillance": (1) personal safety; (2) suicurity[29]; (3) personal efficiency, e.g. using "little data" like distributed blockchain, in an "Internet of People".

VIII. Conclusion

We proposed integral kinesiology for weight training. Participants were representative of bench press users from novice to experienced. We found that introducing integral kinesiology to weight training reduced the overall absement in pitch over time, while also increasing total time taken to complete repetitions of a bench press, and also increasing absement in other axes of the barbell lift (i.e. yaw). Together, these findings suggest that a closed loop feedback system for weight training may provide benefits to the user, increasing their time spent under tension and decreasing the errors made during weight training. It also offers insight into the potential utility of feedback systems that deliver multiple levels of feedback to optimize the lift and minimize error in proper form. Based on the promising results of the closed loop feedback system within individual users, we developed additional applications for integral kinesiology feedback for exercise in larger groups. We propose that real time feedback systems, individualized or used collectively, increase initiation, maintenance, and social benefits to exercise regimes, and thus benefit human health, and eHealth monitoring[21].

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