Accurate Sled Velocity on a Short-Inclined Track Using Accelerometer Data

Part of an Automated Bob-Skeleton Push-Start Performance Monitoring System

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***Abstract*—Wireless Inertial Measurement Units (WIMUs) are increasingly used to gather data and improve understanding of various human performance and complex motion scenarios. The Bob-Skeleton Push-Start features a stooped sprint from a crouch while pushing a heavy sled. Maximizing velocity during this brief period is considered crucial to performance, however it is poorly understood. An adjustable sled Push-Start training tool was instrumented with custom WIMUs, and a test subject performed 36 runs, with 12 combinations of 3 Incline and 4 Weight settings. A developed algorithm automatically identified, extracted, and integrated Pushing-Phase Acceleration data to Velocity and Displacement at hundreds of samples per second. Drift correction methods improved accuracy; while additional checks rejected problematic data-files. WIMU derived Average Velocities were within -0.005±0.074 meters per second (0.319±4.214%) of an existing Light-Gate system. Such an accurate, automatic, WIMU-based system could supplement or replace Light-Gate or other performance monitoring methods, while being more portable and readily usable by coaches or athletes. This would enable consistent, low-cost and high-fidelity, performance monitoring from the gym to the ice-track for improved candidate selection, comparison and training in Bob-Skeleton and other ice-track sled sports.**

Keywords; WIMU, Accelerometer, Bob-Skeleton, Sled, Error Correction, Performance Monitoring.

I. INTRODUCTION

Bob-Skeleton is an ice-track sledding sport – similar to Bob-sleigh, Luge and Toboggan – with a single athlete riding an open sled in a face-forward, prone manner. Each run begins with the Push-Start (PS), which requires the athlete to sprint from stationary, in a crouched position, accelerating to maximum velocity, over a short distance (~30-45m), while pushing a heavy sled (~30-40kg), before transitioning to riding the sled through a series of turns for the remainder of the up to 1.5km long track.

The sport is highly competitive, with the top times over the roughly 90 second run duration often within a fraction of a second of each other. While low PS time is generally believed to be the most crucial aspect of final race time [1], [2], this motion is poorly understood. A combination of the sport's small size and difficulty in accessing ice-tracks, as well as the lack of available data are likely responsible for the lack of detailed PS studies. Relevant publications often rely on problematic data sources, such as: official timing (which ignores the first 15 meters) [1], [3-5]; alternative single interval timing (which hampers direct comparison, or understanding of subtle changes) [6], [7]; or use complex and costly data gathering systems (preventing more widespread use) [8-10].

As such, we set out to develop an easy-to-use, portable system that can provide high-quality sled velocity data. Ideally "On-Ice" performance would be investigated, however "Dry-Land" methods are more likely to be used for selection, comparison and training of Bob-Skeleton athletes [11-13] – especially for new athletes or in countries without a well-established amateur Bob-Skeleton system or easy access to ice-tracks – so initial system development and data gathering used such facilities at the University of Bath.

The "Assassin – Horizontal Power Trainer" is a PS training tool. It consists of a sled which runs along a pair of parallel straight rails, allowing a 3 meter free travel length before impacting attached buffers, with a Light-Gate pair covering the majority of this; additional weights and adjustable track incline can be used to change pushing resistance (See Fig. 1 and 2).

Wireless Inertial Measurement Units (WIMUs) are small electronic devices containing sensing elements, similar to those in smart-phones (e.g., Accelerometers, Gyroscopes,

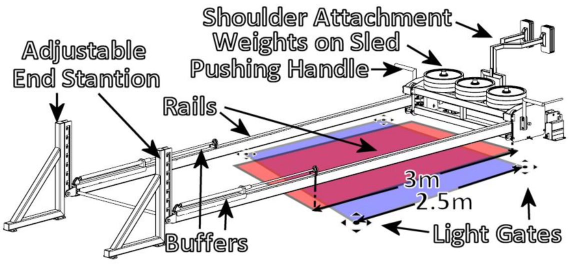

Figure 1. Labelled Diagram of Assassin.

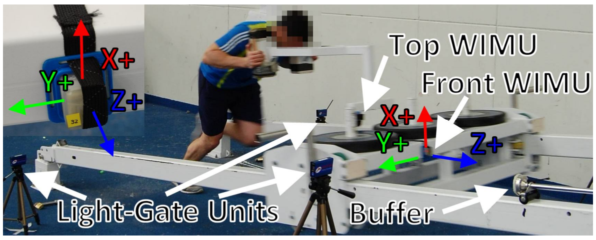

Figure 2. Attached WIMU (inset) and Assassin during Pushing-Phase.

and Magnetometers), along with supporting components, which can act as un-tethered motion sensors. A custom WIMU system was built on the Tyndall 25mm Mote Micro-System platform as part of on-going work on human motion capture for health and sports applications [14-19]; laboratory calibration was performed during assembly [20]. These were attached to the Assassin Sled for PS data gathering.

An automatic process allowing for performance to be accurately quantified using WIMU data recorded from an Assassin run was developed. High sampling rates provided detailed information on how velocity develops from standstill, which could be crucial in determining the subtle effect of changes to training, warm-up and pushing technique and giving a competitive edge.

WIMU derived results were validated by comparing sled Average Velocities to an existing Light-Gate system. An initial target of accuracy within 0.1 meters per second was set as this was considered the threshold for indicating notable differences in performance levels and effectiveness of coaching interventions.

In Section 2, "Data Sources and Method", the equipment, setup, subject and procedure are described. Section 3, "Analysis", contains the acceleration features of a run, segmentation and processing of WIMU data, estimating the full run duration, rejecting runs and the adaptive integration process. Section 4, "Results", explains and provides, individual and combined contour graphs as well as the quantification method used to compare and assess the accuracy of final integrated WIMU data against the Light-Gate and a brief estimation of Light-Gate accuracy. Sections 5 and 6 contain a brief "Discussion" and "Conclusion".

II. DATA SOURCES AND METHOD

A. WIMUs, Location and Orientation

Several identical WIMUs were configured to provide wireless Accelerometer data at the maximum sample rate and sensor range, of up to 256 Hertz and ±16g respectively, reducing the likelihood of saturation and under-sampling of large-magnitude or high-frequency acceleration features. The effective sampling rate varied, being dependant on unpredictable events such as wireless packet loss. Data was streamed via 802.15.4 compatible radio at 2.45GHz to a Base-station connected to a notebook computer. APIs and scripts – written in Python – enabled WIMU configuration as well as sensor data gathering, processing and storage. All sensor data were converted to real world units – using previously gathered on-board laboratory calibration values – and written to file.

Two WIMUs (Front and Top) were placed into 3D-printed holders before being secured to the metal spars of the moveable sled, with similar orientation, using Velcro-elastic straps and tape as shown in Fig. 2. This provided some measure of redundancy and allowed for investigation of the effect of WIMU placement.

B. Other Equipment and Data Sources

A Brower "Timing Centre" Light-Gate system [21] – consisting of 2 emitter and receiver beam sets – positioned to cover the central 2.5 meter portion of each run (See Fig. 1 and 2). Light-Gate ground separation and rail heights were measured using a surveyor's tape to the nearest centimeter. Nominal inclination angles and free travel length were taken from technical drawings of the Assassin.

C. Subject

A fit male was used as the test subject, representing a potential Bob-skeleton athlete undergoing selection. He was familiar-with and trained-in the use-of the Assassin, and was part of on-going sports science and performance research programs at the University Of Bath and UK Sports which these tests were a part of. The purpose, procedures and equipment were explained to him and he had opportunity to ask questions or suggest changes to the procedure. He was also allowed to warm-up, take breaks, perform practice runs or stop the testing at his discretion.

D. Procedure

36 test runs were planned, with 3 runs at each combination of 3 nominal rail angles (0, 4 and 7°), and 4 weight settings (0, 20, 40 and 60 Kg). This allowed for adjustment of the effort required of the test subject. The centrally located padded shoulder pushing attachment was used and the buffers were positioned for the maximum sled free travel length of 3m to provide WIMU datasets with the largest number of samples possible. The test procedure was as follows:

1. Sled is at rest at starting point
2. Change Weight and Inclination Settings if needed
3. Reset WIMUs and Light-Gates
4. Test subject proceeds when ready
5. Stop WIMU recording after the end of the run

III. ANALYSIS

Initial manual review of data established appropriate processing strategies and identified consistent events or features of interest as described below and in Fig. 3.

A. Overview of an Assassin Run

- Pre-Push-Off (PPO): Region with sled at rest at the start of the track, mostly quiescent with occasional motion artifacts due to the athlete addressing the sled. Quiescent

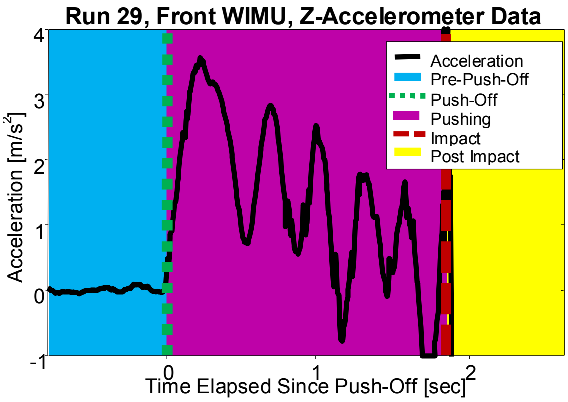

Figure 3. Labelled Main Features of Assassin Run.

sensor level is affected by track inclination.

- Push-off (PO): The start of Pushing-Phase, located at the beginning of a sudden rise in acceleration from PPO quiescent levels.
- Pushing-Phase (PP): Region lasting roughly 2 seconds, with large, cyclical, acceleration features likely due to individual steps.
- Impact Point (IP): A sudden large acceleration feature when the sled contacts the buffers, sensor saturation is common.
- Post Impact (PIP): The remaining data, often beginning with saturated severe oscillations which damp down as the sled comes to a stop, possibly followed by quiescent data and motion artifacts.

B. *Real-World Data Processing Considerations*

Using the equations of motion, it should be possible to integrate all the recorded Accelerometer samples over time to yield sled Velocity and Displacement. However, the recorded WIMU data is not perfect, due to limited sampling rates and sensor range, with additional errors due to sensor noise and quantization further contributing to this. When such data is integrated it tends to drift further from the actual values as these errors compound, increasing greatly over time. These issues are often encountered with WIMU sensors and mitigation strategies have been developed to compensate. A new methodology applicable in Bob-Skeleton and in the more general case is proposed here involving application specific adjustments and integration limits during processing which leads to significantly improved results.

By performing integration only within regions of interest where sensor data is not saturated – in this case the PP between PO and IP – the potential for drift caused by orientation changes, motion artifacts and saturation is reduced. Knowledge of the track inclination angle or the average value of quiescent sections of the Pre-Push-Off region can be used as a Sensor Offset to improve results.

Using known physical limits as integration constraints can further increase the accuracy of the results. In the case of the system described: Initial Velocity and Displacement values are 0, negative Velocity or Displacement values are not possible and Displacement at impact should equal the sled's free travel length (3 meters).

Re-estimation of the integration period to account for data loss etc. causing differences between requested and effective sampling rates can also be used – essentially acting as Time Warping – although this requires an estimate of the duration over which a known number of samples were recorded.

While segmentation and identification of the previously described run features and adjustments to improve the accuracy of results could be performed "by-eye" or manually, an automated method is desirable to reduce subjective human variability and enable development of a self-contained high-accuracy performance monitoring system suitable for use by athletes and trainers.

C. *Automated Data AnalysisMethodology*

An automated analysis system was implemented in the Python programming language. It consists of several stages: Pre-Processing; Impact Detection; Run Segmentation; Start Detection; Integration and an additional stage of Evaluation versus the Light-Gate, as described below and illustrated in the flowchart in Fig. 4.

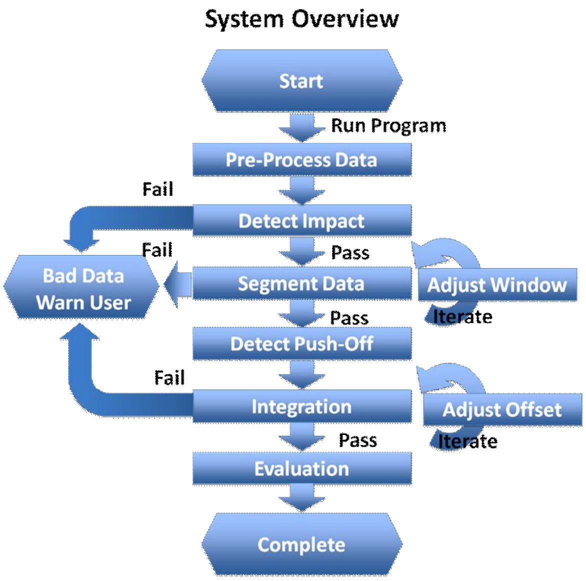

Figure 4. Simplified Flowchart of Assassin Data Analysis Algorithm.

1) *Pre-Processing*

Data are prepared for subsequent analysis. WIMU sensor data are converted to more convenient units, filtered to remove outliers and smoothed to reduce noise, simplifying subsequent integration, segmentation, and feature detection stages. Data from other sources such as Light-Gate timing, Assassin settings and physical measurements; are used to estimate useful values.

2) *Impact Detection*

The largest magnitude Acceleration features are identified as Impact Candidates. A threshold is used to check if these are suitably large.

3) *Segmentation*

Contiguous Active and Passive regions of sensor data are identified using detection thresholds estimated from the most quiescent region of the filtered sensor data. From these, the Active region that contains sufficient data between its start and an Impact Candidate is identified as the PP. If segmentation is unsuccessful, an iterative process attempts to determine a new threshold.

4) *Push-Off Detection*

The region around the PPO-PP transition is searched for a characteristic peak in the smoothed Acceleration data, the beginning of this feature being the Push-Off.

5) *Integration*

Initial conditions are set, the offset is applied and integration is performed using the previously decided integration period and standard equations of motion to yield

Sled Velocity and Displacement at each PP Accelerometer sample. Comparing the estimated and known Displacement at IP allows iterative refinement of the Sensor Offset to yield improved integration results.

6) Evaluation

The integrated data corresponding to the region between the Light-Gates can be extracted from the WIMU Sled Displacement data and the known Light-Gate positions. The WIMU derived Sled Average Velocity values within this region can then be calculated and compared to Light-Gate derived values.

D. Estimation of Full Run Duration

Ideally, the integration period would be the inverse of requested sample rate. However, variable on-device sampling rate and wireless data loss can make this a poor estimate of the system's effective sample period. Improved estimates can be made using per-sample times, or known sample counts and durations; however the system used lacked accurate time-stamping, preventing such direct estimations of effective integration period.

Light-Gate durations and preliminary WIMU integration data were instead used. From the 52 valid WIMU data-files, the average sample count in the Light-Gate region was estimated at approximately 67.7% (standard deviation of 1.9%) of the full run sample count (Table 1). An initial estimate of the expected Full Run Duration for each Assassin setting could then be provided by dividing the Light-Gate timing value by 0.677, dividing PP sample count by this gave an estimate of the Integration Period. Using the final integrated data, the validity of the timed region fractional duration estimate was checked (See Fig. 5), with a best-fit line showing similar results to the initial estimate as can be seen in Table 1. An improved WIMU system with improved time-stamping would allow direct determination of sample period, removing the current implementation's reliance on the Light-Gates for estimating these.

TABLE I. TIMING REGION DURATION ESTIMATES

Run Dur. [%]	*Pre-LG 1*	*Post-LG 2*	*Un-Timed*	*Timed*
Initial Est.	27.3	5.1	32.3	67.7
Std. Dev.	2.24	0.50	1.90	1.90
Final Check	25.72	5.32	31.05	68.95

a. Estimates of Region Average Durations as Percentage of Pushing-Phase Duration

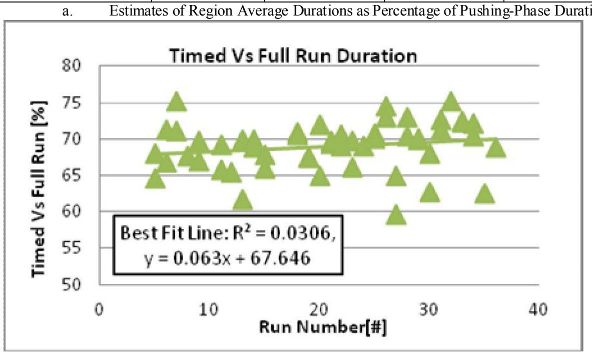

Figure 5. Timed Region Duration Estimates Based on WIMU Results.

E. Identification of Valid Data

Not all recorded data-sets were of sufficient quality to yield reliable integration results. A fully automated system should be able to distinguish good and bad data to ensure valid results are generated. Several poor data rejection conditions were identified, with suitable tests performed during analysis and warnings provided as follows:

1) Missing Events in WIMU Data

Recording started too late or finished too early, cutting off PO or IP, causing failure during event detection stages.

2) Missing Data from Other Sources

Other essential data was un-available (i.e. Light-Gate).

3) Excess Data Loss

PP had less than 50% of the data samples expected.

F. Integration Process

An initial estimate of sensor offset is made based on the average value of passive sensor samples in the PPO region (1). The initial offset is applied to each PP sensor sample but will be iteratively refined later.

$$acc_{offset} = \frac{\sum_{k=0}^{N} acc_k}{N} [m/s^2] \qquad (1)$$

For N Quiescent raw sample values, acc_k, in PPO Region

An integration period that accounts for wireless data loss, removal of bad sensor samples or WIMU internal issues that change the effective sample rate is needed. From the PP sample count and full run duration we can estimate an effective sample rate for each data-file and hence integration period (2). However, without accurate sensor data time-stamping we must use Light-Gate timing data estimations of the full run duration.

$$t = \frac{T_{PP}}{i_{PP}} = \frac{T_{IP} - T_{PO}}{i_{IP} - i_{PO}} \approx \frac{T_{LG}/0.677}{i_{IP} - i_{PO}} \qquad (2)$$

For Integration Period t, Time T and Sensor Sample i

Then integration of PP WIMU data can begin, converting offset adjusted Acceleration a, to Velocity v (3) and Displacement s (4) for the n^{th} sensor sample since PO.

$$v_n = v_{n-1} + a_n t \qquad (3)$$

$$s_n = s_{n-1} + v_{n-1} t + ½ a_n t^2 \qquad (4)$$

Known and WIMU estimated Displacement at Impact are compared to each other and used to refine the Offset value in an iterative binary search manner. This process is explained in the C-style pseudo-code in Fig. 6.

```
WHILE( !complete && i<max_iteration ){
 IF( ABS(displ_error) >= target_accuracy ){
  IF(displ_error > 0){
   test_offset = offset - offset_step;}
  }ELSE{ // displ_error < 0
   test_offset = offset + offset_step;}
```

```
  z_vel = itegrate(z_acc, test_offset, period);
  z_displ=integrate(z_vel, test_offset, period);
  impact_displ = z_displ[-1];
  new_error = impact_displ - target_displ;
  IF( ABS(new_error) < ABS(displ_error) ){
   offset = test_offset;     // update offset
   displ_error = new_error;} // update error
  offset_step /= 2;
  i++;
 }ELSE{ // ABS(displ_error) < target_accuracy
  complete=True ;} }
```

Figure 6. Iterative Sensor Offset Refinement

IV. RESULTS

Of the 70 data-files processed, 52 were determined to contain valid PP data, all of which were segmented successfully on the first attempt, with 12.17 (Standard Deviation 0.98) sensor offset refinement iterations required. Samples of output shows the WIMU and Light-Gate derived average velocity over the timed region (indicated by height of cyan shaded region and horizontal cyan dashed line respectively) are very similar, having a difference of $0.06 m/s^2$ (see Fig. 7).

Contour graphs of mean Light-Gate and WIMU derived Sled Average Velocity for each Weight and Inclination setting (See Fig. 8 and 9) show similar magnitudes and a trend for reduced velocity with increasing resistance (i.e. additional Weight and steeper Inclination) with average difference of -0.005±0.074 meters per second. The Root Mean Squared Error (RMSE) between the two (See Fig. 10) better illustrates this high similarity, with a maximum error of 0.105 m/s, most results are well within the target accuracy level of 0.1 m/s across a wide range of speeds and equipment settings used.

A. *Light-Gate Un-Certainty*

The Light-Gate derived Sled Average Velocity is not exact, as both the timing and distance measurements required have an associated uncertainty. The time is given in seconds to two places of decimals so estimated un-certainty is 0.01 seconds. The un-certainty in the distance travelled by the sled, due to errors in positioning the Light-Gates on 1m tall tripods, was estimated at 0.02 meters. Additionally, inclination affecting the rail length between the Light-Gates was trigonometrically estimated as approximately 0.02 meters (2.5 meters at 0° versus 2.519 meters at 7°). Adding these gives an overall maximum distance error estimate of 0.04 meters. By combining the lower time with upper distance estimates and vice-versa, the un-certainty in Light-Gate Derived Sled Average Velocity was estimated as ranging from 0.066 to 0.115 meters per second (±2.3% on average) (See Table II).

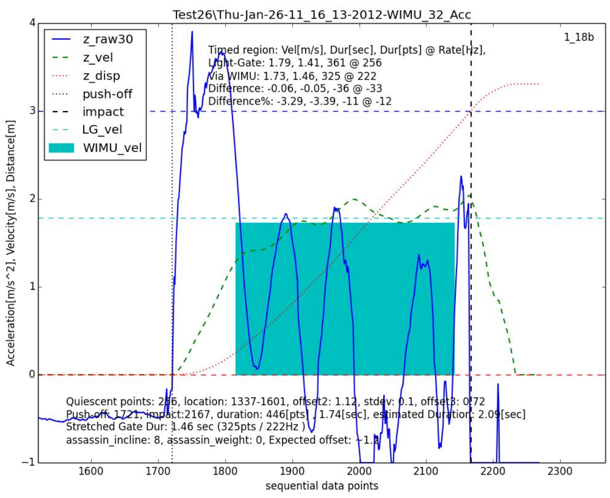

Figure 7. Processed Run showing Good Average Velocity Agreement.

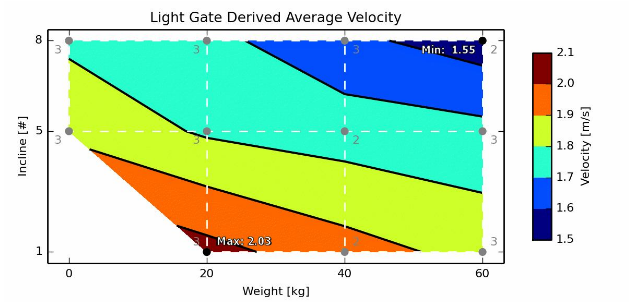

Figure 8. Timed region Light-Gate derived Average Sled Velocity.

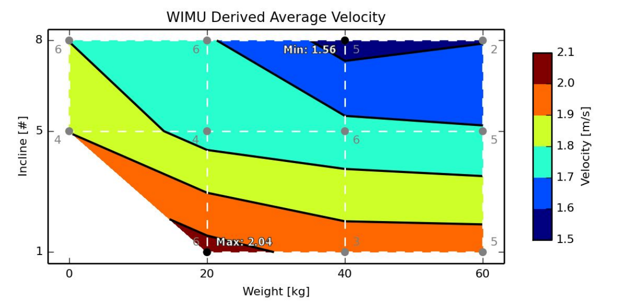

Figure 9. Timed region WIMU derived Average Sled Velocity

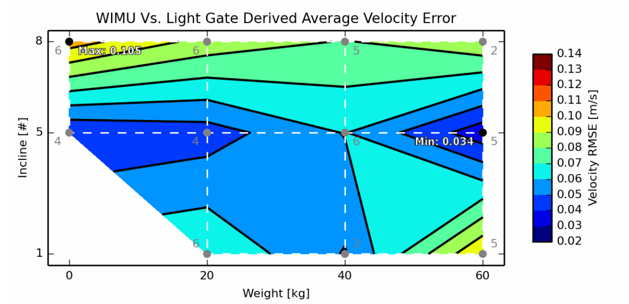

Figure 10. RMSE of Sled Average Velocity for the 2 Methods. White regions indicates no data available, gray numbers denote number of samples used to produce value.

TABLE II. LIGHT-GATE UNCERTAINTY ESTIMATES

For 2.5±0.04 m	*Duration [sec]*	*Velocity [m/s]*	*Un-Certainty*
Slowest	1.67±0.01	1.497±0.066	±2.199%
Fastest	1.09±0.01	2.294±0.115	±2.518%
Average	1.43±0.01	1.748±0.080	±2.300%

V. DISCUSSION

WIMU and Light-Gate differences are low, generally within the target and often within the Light-Gate uncertainty levels. Additionally WIMU data provides a more complete picture of the Pushing-Phase, yielding velocity and displacement at each sensor sample. This enables the creation of arbitrary virtual timing intervals; analysis of the development of velocity; the detection of individual step features, etc. Future WIMU based systems could be even more low-cost, small and self-contained than that developed here; allowing use across gym, test-track and on-ice sleds, without requiring trained users, extensive sled modifications or costly installation of trackside equipment. Such a system holds great potential for: improving the understanding of the Push-Start; identifying good athletes and determining the effectiveness of coaching and training interventions.

VI. CONCLUSION

Although the Bob-Skeleton Push-Start is considered crucial to performance, it is poorly understood due to a lack of detailed data or accessible methods for gathering such data. Using WIMUs to instrument Assassin a method for automatic segmentation, drift correction and integration of Accelerometer data to Velocity and Displacement was developed. Sled Average Velocity results were similar to Light-Gate with Root Mean Squared Error within or similar to the target accuracy and un-certainty levels. The system's accuracy, low-cost, ease-of-use and portability, could provide greater access to such quantitative performance data, with its highly detailed data enabling improved understanding of the Push-Start. These could lead to improved methods for Selection, comparison and training, potentially providing a valuable competitive edge.

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