Minimal wearable setup via sensor correlation: a case study of field hockey players*

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Abstract

Monitoring athletes with wearable sensors allows to gain insights on their technique and physical condition. However, invasive setups containing a large number of sensors may hinder the mobility of the athletes, leading to under-performance and possibly inaccurate data collection. In this paper, we show that correlation between data collected by different wearables can be used to identify a minimal setup. We propose a methodology to remove the least important sensors, and apply it to data collected by monitoring field hockey players. In this study, the number of sensors was reduced from 23 to 8 by deleting those exhibiting a correlation above 98%. Additionally, we demonstrate that even with a minimal sensor configuration, a significant amount of information is retained with regards to predicting the ball speed following a drag-flick, an important technique in field hockey. Our experiments indicate that the utility of the data for this specific task remains practically unaltered.

Keywords

wearable sensors, data analysis, machine learning

1. Introduction

The utilization of wearable sensors in the study of athletes allows researchers to obtain a comprehensive understanding of their physical condition. These sensors are extensively employed to monitor various health-related parameters, including workload, hydration levels, and heart rate [1, 2]. Researchers have started using sensor setups to not only prevent injuries and illnesses, but also to boost the athletes' performance [3]. The latter objective is mainly achieved through the use of inertial measurement units (IMUs), such as accelerometers and gyroscopes, which are positioned on key points of a subject's body, such as the head, spine, joints, and limbs. IMUs capture spatio-temporal and kinematic data, thereby offering a comprehensive three-dimensional representation of the subject's body movement over time.

A typical setup usually involves the attachment of several IMUs to the subject using a specialized bodysuit. Despite the considerable value of these sensors as a source of information for sports data analysts, wearing such a comprehensive setup may negatively impact the athlete's performance [4, 5, 6]. As a consequence, the collected data may not accurately reflect a typical scenario in which the sensors are not worn, leading to flawed evaluations.

Previous research has explored the possibility of minimizing the number of sensors worn by subjects to reduce the impact on their mobility [7, 8]. However, many of these studies primarily rely on ad-hoc heuristics and observations specific to the application at hand. In this paper, we propose a method for automatically determining a minimal setup based on correlations in IMU measurements. The core idea of our algorithm is to eliminate redundant information by removing sensors that exhibit correlations above a specified threshold.

The contributions of this work are as follows:

- We demonstrate that it is feasible to reduce the necessary sensor setup to monitor field hockey players. Specifically, we focus on the assessment of players performing a "drag-flick", a particularly challenging shot that requires significant coordination.
- We identify the most "insightful" sensors in the minimal setup. We also establish the groups of sensors that are greatly correlated and have limited value for data controllers.
- Finally, we show that the obtained minimal sensor configuration can still effectively predict the ball speed during drag-flick, with only a slight reduction in performance as compared to the complete set of IMUs.

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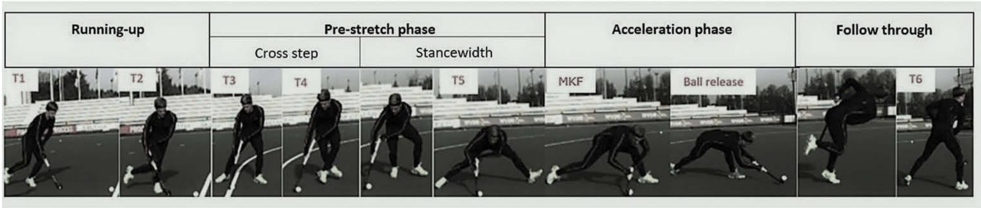

Figure 1: All key events in the execution of a drag-flick. Image obtained from the creators of the dataset [10].

Our experiments are conducted on a real-world sensor dataset, which was collected by field hockey players while practicing the drag-flick.

2. Background and key concepts

In this section we describe the relevant concepts of field hockey and stress the importance of feature selection from raw data.

2.1. Field hockey

Drag-flick. Our work focuses on data collected from field hockey players during their practice of a technique known as the “drag-flick”.

The drag-flick is a highly effective shot in which the ball is lifted above the backboard of the goal rather than simply being hit, making the shot more aggressive at penalty corners. It is one of the most important techniques to be mastered in field hockey and requires coordinated action of multiple body parts. The key stages of a drag-flick can be seen in figure 1. After the acceleration phase T1-T3, T4 begins with the right foot rotating on the ground while the left foot leans as far forward as possible. At T5, the left foot lands on the ground. At the same time, the onset right wrist flexion begins with simultaneous maximal knee flexion, followed by extension. The follow-through of the shot occurs at T6 which concludes the drag-flick. Prior works have demonstrated that the greater the maximal knee flexion angle between T4 and T6, the higher the resulting ball speed. [9].

Examining sensor recordings of a drag-flick shot offers valuable insights into the player’s form. However, an overly invasive IMU setup can lead to subpar performance by the athlete, resulting in inaccurate data. As a result, drag-flick monitoring constitutes the perfect example of a task that could benefit from a reduced sensor setup.

Ball speed prediction. To measure the loss in utility of our minimal sensor setup compared to the original one, we evaluate the performance of ball speed prediction during drag-flick. The speed of the ball in field hockey is considered one of the most important metrics to assess the form of a player. It is typically measured by high-speed cameras or radar systems, and predicting speed based on IMU data is an open problem. Rather than focusing on achieving the lowest possible prediction error, we use ball speed as a target variable to select important IMUs.

2.2. Feature selection

In machine learning, feature selection is the task of identifying relevant input variables (features) in the data. Selecting important features improves the generalization capabilities of models and prevents overfitting. In the context of medical and sports research, however, feature selection can also be used to find relevant sensors from a larger pool of potential IMUs. This allows to reduce redundancy and increase the accuracy of the analysis by only focusing on the most informative IMUs.

Feature selection techniques are divided in three main types: filter methods, wrapper methods, and embedded methods [11]. Filter methods are “a priori”, meaning that they are performed independently of the chosen prediction model. These are usually based on metrics such as correlation or mutual information between individual features and the target variable. Wrapper and embedded methods, conversely, choose the most relevant features based on how much they contribute to the prediction for a specific model.

A comparison of these three types of techniques has been done by prior works [12, 13] and is beyond the scope of this paper. In our work, we aim to show that feature selection can be used to determine a minimal setup of wearable sensors. Adopting a minimal sensor setup has the two-fold advantage of reducing the equipment cost while making it less invasive for the athletes, leading to more accurate and realistic measurements. The feature selection algorithm that we adopted in our analysis is a combination of a univariate filter method and the correlation.

3. Related work

Body sensors and athlete monitoring. The advancement of technology and the continuous need for performance enhancement in sports [14] has accelerated the utilization of wearable sensors in sports data analytics [15, 16, 17]. A sensor network was introduced to monitor important indicators of world-class rowers for different rowing techniques [18]. Schmidt et al. utilized an IMU wearable setup to measure stance duration of both track and field sprinters [19]. The researches managed to identify four different types of basketball shot with 98% accuracy via a micro IMU-based wristband [20].

These devices have also been employed in field hockey, for example to recognize players' activities [21] and to improve their technique. Iwamoto et al. [22] proposed a sensor-based approach to improve the push pass technique. Eight sensors were applied on several contact points of the stick and associated with different feedback sounds. This enabled players to receive real-time feedback on the effectiveness of their pass.

Furthermore, other works before ours focused on the study of the drag-flick technique. Body sensors were also utilized for assisting new players in executing a successful drag-flick [9]. The participants of the study have reported the improvement in the drag-flick technique, a decrease of the body load during the shot, and commended the more interactive learning experience.

Minimal sensor setup and feature selection. Previous works have investigated reducing the number of devices in body sensor configurations. Typically, in these studies, relevant sensors were chosen through feature selection, resulting in an optimal setup for a particular task. In the field of digital healthcare, Caramia et al. [23] utilized feature selection to determine relevant sensors in the recognition of Parkinson's disease using IMU-based devices. Their approach involved separating the sensors into various sub-groups and evaluating their significance in prediction. The significance was determined by calculating the accuracy of various classification algorithms. Khademi et al. [24] aimed to minimize the number of sensors in gait mode recognition. They proposed a novel gradient-based feature selection method, which introduces a penalty for the number of used features in the objective function. This method is applicable only to models that are trained based on gradient descent, such as neural networks. Amjad et al. [25] published a comparative evaluation of feature selection approaches for human activity recognition (HAR). At present, a minimal sensor setup can be realized via a single advanced compound device, such as a fitness tracker. A single wearable devices has been used in a number of lifelog studies, involving both regular participants [26] and professional athletes [27]. Utilizing only a single device for monitoring various parameters tends to be less invasive and equally informative for some applications.

	Year			
	2017	2018	2019	2021
Males	14	13	13	18
Females	9	9	12	9
U16	9	5	15	10
U18	5	7	-	10
U21	6	4	-	6
Seniors	3	6	1	2

Table 1
Demographics and temporal statistics of the DragEXT dataset.

4. Dataset

In our experiments, we utilize a private dataset collected by Kinetic Analysis[1] in collaboration with the Royal Dutch Hockey Association (KNHB). The dataset comprises multiple trials per hockey player collected over four years (2017, 2018, 2019, and 2021), where each trial represents a full execution of a complete drag-flick. Since the dataset was collected over multiple years, henceforth we refer to it as DragEXT (drag-flick extended).

In total, 77 highly capable individuals of various ages participated in the data collection. The following age groups are represented in the dataset: U16 (younger than 16 years old), U18 (16-17 years old), U21 (18-20 years old), and seniors (older than 20 years old). The age and gender breakdown of the hockey players per each year is depicted in table 1.

Overall, more than 1,500 drag-flicks have been recorded, with ball speed measured for at least 1,300 trials. Around 350 drag-flicks have been manually annotated to contain timestamps for all the events typical of a drag-flick (as depicted in figure 1). The trials were recorded using the Moven suit by XSens. In total, 17 IMUs are contained in the suit to monitor various characteristics during the flick, including on the head, sternum, spine, and pelvis, as well as on shoulders, upper arms, forearms, hands, feet, and finally on upper and lower legs. These IMU measurements are combined to form a total of 23 sensor segments. Throughout the paper, we test our algorithm to reduce the number of such sensor segments, which we call just "sensors" for simplicity. We depict the sensors and their on-body placement in more details in table 2. In addition to objective measurements taken by accelerometers and gyroscopes, sensors were also calibrated to record derived measurements of position, velocity, orientation, and some other metrics. Measurements of position and velocity are recorded as 3D coordinates (x, y, and z), while the orientation is measured in quaternions[2]. Sensors were collecting data at the highest available sampling frequency of 240 Hz. Therefore, each trial in the dataset is represented as a set of

[1] https://www.kinetic-analysis.com/
[2] https://base.xsens.com/s/article/MVNX-Version-4-File-Structure

Time index	T4	T4+1	...	T6
Pelvis_acceleration_x (m/s^2)	-0.097955	-0.0637	...	-1.764977
Pelvis_acceleration_y (m/s^2)	-0.192932	-0.062622	...	-0.69426
Pelvis_acceleration_z (m/s^2)	0.263944	0.261898	...	-2.795869
⋮	⋮	⋮	⋮	⋮
Neck_velocity_x (m/s)	-0.100449	-0.100892	...	-0.04733
Neck_velocity_y (m/s)	-0.002497	-0.000822	...	1.206778
Neck_velocity_z (m/s)	-0.015762	-0.013629	...	-0.026338
⋮	⋮	⋮	⋮	⋮

Figure 2: Example of trial recording formatted as a multidimensional time series.

Sensor name	Position	Number
Pelvis	Pelvis	1
Neck	Neck	1
Head	Head	1
T8	Thoracic spine	1
T12	Thoracic spine	1
L3	Lumbar spine	1
L5	Lumbar spine	1
Shoulder	Shoulders	2 (Left, Right)
Upper Arm	Upper arms	2 (Left, Right)
Forearm	Forearms	2 (Left, Right)
Hand	Hands	2 (Left, Right)
Upper Leg	Upper legs	2 (Left, Right)
Lower Leg	Lower legs	2 (Left, Right)
Foot	Feet	2 (Left, Right)
Toe	Toes	2 (Left, Right)

Table 2
The full list of sensors (segments) utilized in the Moven suit by XSens. The bottom half of the sensors are duplicated and placed on both parts of the body. In our reduction methodology we aim to identify the most impactful.

time series for all combinations of available sensors and recorded measurements, totalling 437. For the annotated kicks it is feasible to associate the above time series with the respective events of a drag-flick (T1-T6).

Preprocessing. As a preliminary step, we format the trial recordings as time series data. For all combinations of sensors, measurements, and coordinates in each trial, we extract a sequence of data and format them as a multidimensional time series, as shown in figure 2. Throughout the paper, we refer to the sequences forming the multidimensional time series as "channels". The name of each channel follows the format "sensor_measurement_coordinate", e.g., neck_velocity_x.

Furthermore, for the purpose of predicting the ball speed, we keep only the samples between the key frames T4 (right foot touch during pre-stretch phase) and T6 (end of the drag-flick).

5. Methodology

In this section we describe our methodology for sensor selection, the feature extraction procedure and benchmarks for our models in great details.

5.1. Sensor selection algorithm

Our sensor selection algorithm is divided into two main parts. In the first part, we extract features from sensor time series and we rank them individually, meaning that we only consider how much each feature is related to the target variable (in our case, the ball speed). Then, we construct a histogram with the top k relevant features as in figure 3. This is used to do a preliminary ranking of the sensors, based on the number of highly relevant features that they produce. The extracted features and the method used to rank them may vary depending on the application. The specific method adopted in this study is described in section 6.

In the second part, we discard redundant IMUs based on their correlation in the time domain. For example, by examining the velocity measured by two sensors located on the spine (T8 and T12) in figure 4, one can easily see that they exhibit a strong correlation during the drag-flick. When two sensors are highly correlated, we discard the one lower in ranking. This procedure aims at retaining the sensor which is more likely to produce relevant features.

To efficiently select sensors for the minimal setup, we first sort them by their ranking in terms of relevant features, starting with the top ranked. We delete all the lower-ranked sensors which are above a correlation threshold θ_ρ, which is a parameter of our algorithm. We then repeat the procedure for the non-deleted sensors, ordered by their ranking. The remaining sensors at the end have a pairwise correlation below the chosen threshold. The complete procedure is detailed in algorithm 1.

Indeed, this is a "greedy" algorithm, based on the intuition that sensors producing more relevant features provide higher utility. To find the truly optimal combination of sensors, one would need to try all the possible combinations of uncorrelated sensors, which however is

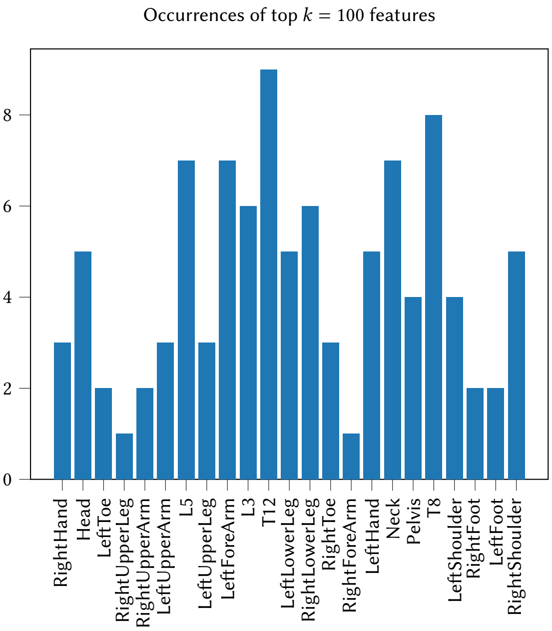

Figure 3: Occurrences of top features extract by each sensor, considering only the velocity components along the three axes.

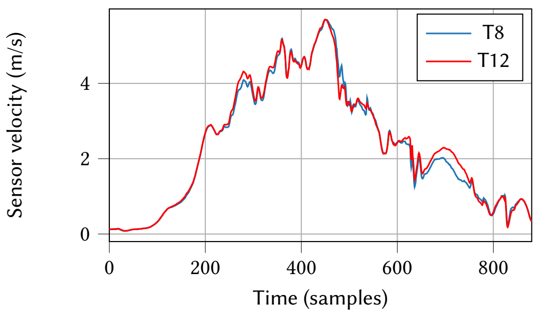

Figure 4: Example of two correlated sensors, T8 and T12, both located on the subject's spine. The graph shows the variation of velocity over time between the beginning of the pre-stretch phase (T_4) and the end of the follow through (T_6) for one specific user and trial. Most examples exhibited similar behaviour.

exponential with respect to the number of sensors in the worst-case scenario.

5.2. Ball speed prediction

In order to test our sensor selection algorithm, we assess the performance of basic machine learning models that predict the ball speed before and after reducing the

Algorithm 1 Sensor selection

procedure SensorSelection(list of sensors S ordered by ranking, threshold θ_ρ)
    $\bar{S} \leftarrow S$ ▷ Initialize the final list of sensors
    for s in S **do**
        if s not in $\bar{S}$ **then**
            continue   ▷ Skip to the next iteration
        for s' in $\bar{S}$ **do**
            if $s \neq s' \wedge \mathrm{corr}(s, s') > \theta_\rho$ **then**
                Remove s' from $\bar{S}$
    return $\bar{S}$

number of IMUs. Ideally, the sensor selection algorithm should mostly remove redundant information from the IMUs, leaving the performance of the models almost unaltered. In other words, a smaller loss in accuracy is an indicator that our algorithm is effectively removing duplicate information.

Metrics. Predicting the ball speed is a regression problem. In order to quantify the performance of regression models on this task, we adopt two widely used error metrics, namely mean average error (MAE) and root mean squared error (RMSE). Calling $y_1, \ldots, y_n$ the ball speed measurements over n trials, and $\hat{y}_1, \ldots, \hat{y}_n$ the corresponding predictions of a regression model, the MAE is computed as

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n} |y_j - \hat{y}_j| \tag{1}$$

while the RMSE is computed as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n} (y_j - \hat{y}_j)^2}. \tag{2}$$

Both metrics are important to provide an overall understanding of a regressor's performance. The main difference between the two is that RMSE tends to be more sensitive than MAE to infrequent large errors, meaning that it can be significant if there are few outliers in the dataset. As a baseline for both metrics, we consider the performance of a naive regressor that always predicts the average ball speed (i.e., 81.52 km/h). This regressor yields a MAE of 9.68 km/h and a RMSE of 12.09 km/h. Any regression model providing higher error values should be considered non-informative.

6. Experiments

In this section, we apply our sensor selection algorithm to the DragEXT dataset. To evaluate the full sensor setup, we utilize all the IMUs and keep the overall top-100 features. The precise procedure for feature extraction is detailed in section 6.1.

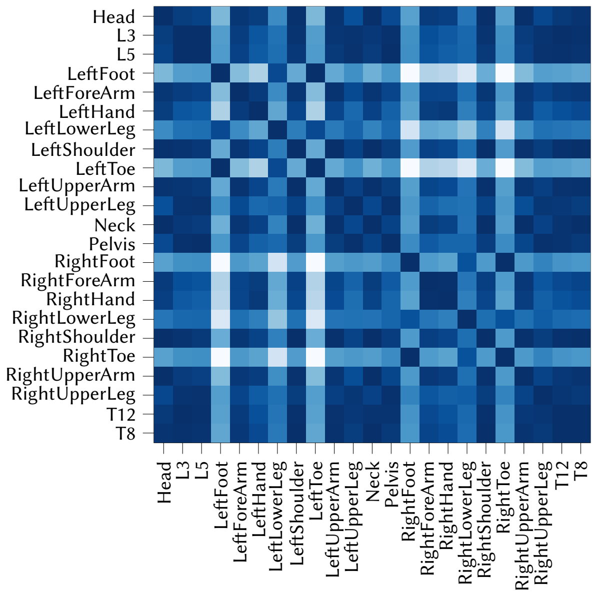

Figure 5: Correlation matrix showing Pearson's correlation between different sensor's velocity. Darker colors imply a higher correlation.

In order to assess the minimal sensor setup we repeat the feature extraction process (again, extracting the top-100 features) after applying algorithm 1 on the full set of IMUs.

6.1. Feature extraction and ranking

In order to extract features from our time-series data, we utilize the TSFresh Python package[3]. With default parameters, TSFresh extracts 783 features for each channel of a multidimensional time series, including peak values, minima, autocorrelation, quantiles, and more. Counting all the sensors, measurements, and coordinates, each trial's timeseries comprises 437 channels. If all the possible features were to be extracted, they would be over 340,000, making the dataset imbalanced in width and hard to process.

Therefore, as a preliminary selection, we keep only the velocity measurements. Since estimation of position, velocity, and acceleration over time provide an equal description of the motion, keeping only one of them should not reduce the amount of information in the time series. Regarding orientation, preliminary experiments showed that including it does not have a major impact on the results. Therefore, we decided to not include such measurements.

After extracting all the features from the velocity measurements with TSFresh, we select the top $k = 100$ relevant ones, ranking them individually. We calculate Kendall's tau [28] between each feature and the ball speed, and rank them according to the obtained p-values.

6.2. Models evaluation

Once the top 100 features are extracted, we evaluate the performance of multiple regression models using 10-fold cross-validation. Normally cross-validation is used to tune the hyperparameters of a model, but in this case we adopt it to evaluate models without choosing a specific train-test split. It is important to note that our goal is to assess the expected performance of several regressors, not to obtain a ready-to-deploy model.

6.3. Results

Minimal setup. We ran our sensor selection algorithm using the absolute value of Pearson correlation for the correlation metric, i.e., for two sensors s, s' we computed

$$\mathrm{corr}(s, s') = \left| \frac{\sum_{t=1}^{T} s[t], s'[t]}{\sqrt{(\sum_{t=1}^{T} s[t])^2 (\sum_{t=1}^{T} s'[t]^2)}} \right|, \qquad (3)$$

where t is the time index within the time series. The time series used for comparing sensors is the magnitude of the sensors' velocity. In other applications, Pearson correlation may not be a suitable metric, since it does not account for shifts or delays in possibly correlated time series. However, in the case of DragEXT, IMUs were taking

[3]https://tsfresh.readthedocs.io

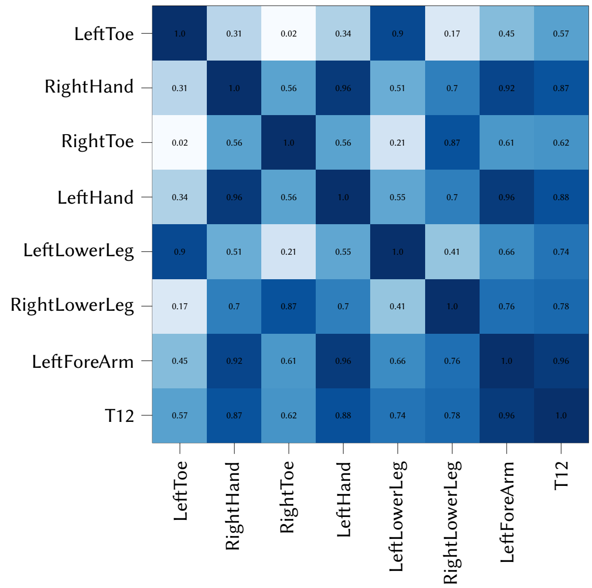

Figure 6: Correlation matrix after removing sensors which had over 98% correlation (in absolute value) with other sensors. The sensor located on the leading knee (right lower leg) is preserved, confirming previous studies that underlined its importance [10].

measurements synchronously, thus correlated time series were always aligned. The Pearson correlation computed between different sensors can be seen in figure 5.

After eliminating all the sensors above a threshold of 98% correlation, the minimal setup identified by our algorithm results in 8 sensors, namely those attached to left toe, right toe, left hand, right hand, left lower leg, right lower leg, left forearm, and T12 (located on the spine). The correlation matrix between the IMUs in the minimal setup is shown in figure 6. Notably, the T8 sensor has been removed, being highly correlated with T12 as shown in figure 4.

Errors in ball speed prediction. We evaluate a number of regressors before and after applying our sensor selection algorithms. These include widely-used machine learning models such as linear regression, decision trees, random forests, and k-nearest neighbors. The complete list, along with the validation performance in terms of MAE and RMSE, can be seen in table 3.

The minimal setup obtained by our algorithm generally provides a slightly higher error, both in terms of MAE and RMSE, compared to the complete sensor setup. However, it is notable that such errors are still considerably smaller than the baseline, indicating that most of the data utility has been preserved. Additionally, some simple models such as ridge and lasso regression (which are essentially regularized linear regression models) are outperforming the complete setup. These models are typically more interpretable, providing practical insights. For instance, prior works have considered linear models to study the relationship between lead-knee extension and ball speed [10]. Finally, our algorithm produces a setup requiring one third of the sensors compared to the full set of IMUs, reducing them from 23 to 8.

7. Discussion

Quality and quantity of sensors in the setup. Naturally, the ideal minimal setup may differ depending on the task at hand. For example, some problems may require as many various measurements as possible regardless of the invasiveness of IMUs. For others it is much more vital to ensure convenience and mobility of the athletes by wearing limited number of the sensors. Since the proposed algorithm of sensor selection makes use of the correlation threshold θ_ρ, our approach enables data controllers to balance the tradeoff between number of IMUs and the athletes' comfort.

Varying sensor setups for different sports. Depending on the required levels of mobility, the setup proposed for field hockey may not be an ideal solution for other sports. For instance, for some sedentary disciplines like chess and racing organizers tend to mandate athletes to wear specific on-body sensors regardless of their invasiveness [29, 30]. Therefore, the likely optimal setups are discipline-specific and need to be established separately. We believe our approach may be tuned to other sports

	MAE		RMSE	
	All sensors	Minimal setup	All sensors	Minimal setup
Decision Trees	6.0687	6.1921	7.9471	8.6492
Random Forests	**4.3685**	5.0673	**5.7409**	6.5677
Extra Trees	4.4192	4.6089	5.7773	6.0308
Gradient Boosting	4.7308	4.9489	6.2820	6.4902
AdaBoost	5.0561	5.2294	6.4369	6.6559
k-Nearest Neighbors	5.3813	7.6121	6.8486	9.7397
Linear Regression	7.8707	6.8092	10.3629	9.1127
Ridge Regression	6.5187	6.3209	8.6161	8.4516
Lasso Regression	6.7009	6.4632	8.2779	7.9538
Baseline	9.6750		12.0863	

Table 3
Results obtained by different machine learning algorithms in terms of MAE and RMSE. These results represent the average performance on the validation set for 10-fold cross-validation.

and encourage researchers from other domains to investigate the problem of sensor reduction.
Mirroring optimal sensors. Again, we establish the best 8 sensors for the minimal setup to be those attached to left/right toe, left/right hand, left/right lower leg, left forearm, and T12 (spine-based). Interestingly, for those sensors that do have counterparts on the opposite side of the body, our algorithm recognized both of them as most important except for the one located on left forearm. Since not all the players who took part in the data collection were right-handed, it does appear logical for the optimal setup to be mirrored with respect to both hands to not overemphasize the dominant hand for the majority of the players. Therefore, we believe that despite the sensor on right forearm to not be selected by the algorithm as the top-8 IMUs, it should be added to the final setup to ensure fairness with respect to minority players.
Future work. The future research includes experimenting on other tasks in field hockey. Since, at present, the problem of annotating the events during drag-flick is typically being done manually, we consider to extend our approach to automatically detect stages of the shot. We further plan to combine the research of minimizing the number of the sensors in the setup with the event segmentation tasks. Finally, we would like to collect a new dataset with both full and minimal sensors setups for the same users to assess the comfort of players and measure whether they exhibit any improvement during field hockey tasks.

8. Conclusion

In this work we explored the possibility of reducing the required intertial measurement units (IMUs) to monitor field-hockey players. Specifically, we focused on a minimal setup to assess players' form while executing a drag-flick. Our approach eliminates the sensors that are heavily correlated, retaining only the most important ones. We showed that it is feasible to reach comparable results for ball speed prediction in field hockey with both full and minimal sensor setups. We experimentally demonstrated that for some of the models achieve better performance with the minimal setup. Our sensor selection approach can be employed for other sports and other tasks that require the use of IMUs.

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