An Intelligent System for Motor Style Assessment and Training from Inertial Sensor Data in Intermediate Level Ski Jumping

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Abstract: In this research we developed a wearable, augmented motion feedback system for ubiquitous training and motion assessment in mid-level ski jumping. Ski jump motion data captured with a set of inertial sensors were first transformed into meaningful kinematic motion information using an extensive processing system. Next, derived segment orientations, joint positions and joint angles were used to build and train motion knowledge on the base of the sport's common style and judging criteria. This intelligent machine knowledge was then applied to identify specific style information within incoming motion data that could be provided to the athlete as augmented motion feedback via a mobile training application. System validations on a set of test jumping data showed that style errors could be recognized and displayed well by the implemented system. We therefore believe the system to be suitable for the provision of kinematic motion feedback that could not be obtained without an extensive training support environment otherwise. Adding a real-time environment for athlete-system communication, this could lead to the creation of an ubiquitous training support application in future.

1 INTRODUCTION

The enhancement of motor skill acquisition and motor learning by additional and augmented performance feedback is one of the most interesting objectives for technological support in sports. Particularly important for the implementation of future training applications is the development of techniques that provide motion information on an easy-to-use basis. This problem comprises both the use of wearable capture devices that can be employed under any environmental condition, and the processing of raw numerical motion data into intuitive data output. In this work, we addressed both aspects with the intention of implementing a mobile style assessment and training support system for intermediate and junior level ski jumping.

Ski jumping is a very technical sport that is defined by biomechanical and physical laws (e.g. drag and lift) to a large extend. Erroneous motion execution and use of aerodynamic forces immediately influence the performance and can furthermore increase the risk of fall and injury. However to date, knowledge about ski jumping is mainly based on practical experience, simulations and wind tunnel measurements (Seo et al., 2004; Marqués-Bruna and Grimshaw, 2009b; Marqués-Bruna and Grimshaw, 2009a). Exact kinematic and dynamic properties of an athlete are quite difficult to measure during the actual jump. This is due to the sport's large field of motion activity as well as unstable weather and daylight conditions. They do not allow for quality data from conventional video or optical motion capture systems. As a result, computer based motion analysis methods for ski jumping are effectively non-existent so far, and the assessment of a jumping performance is still a mainly visual task.

By making detailed and accurate ubiquitous motion information available to coaches and athletes, new training standards could be set. In ski jumping, we consider a mobile feedback platform as particularly beneficial for junior and intermediate level athletes. Here, economical and logistical constraints influence the quality of the general training structures: for example it is common that many jumps are executed within a very short span of time. Consequently, responsible coaches often observe jumps from one perspective only (generally the coaches' stand), while the assessment of every single jump performance has to be instantaneous. Internal motor representations in intermediate level jumpers on the other hand are less stable than in professional athletes, making additional

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information on previous motion performances a very valuable feedback in future. Therefore, the aim of this work was to develop a wearable framework for application in motor style assessment and training of mid-level ski jumping.

2 DATA COLLECTION

85 ski jumps were collected during summer ski jump season from four different junior athletes (three ski jumpers and one Nordic Combined athlete) at a normal hill with a K-point (indicating the hill's steepest point) of 90 meters. The motion of every athlete was captured with nine waterproof inertial measurement units of 16 bit quantization rate (Logical Product, 2015). The measurement units were of 67x26x8 mm size and 20 g weight and had an internal memory capacity of 32 MB with an average operation time of 3 hours. Every device contained triads of gyroscopes, accelerometer and magnetometer for the respective x, y and z axes. The gyroscopes were specified with a full-scale range of ±1500 dps with 0.67 mV/dps sensitivity. Accelerometer specification varied in dependence on the placement between either a minimum full-scale range of ±5 G (body placement) or ±16 G (ski placement) with 191.7 mV/G sensitivity. Magnetic field sensors had ±1.2 Ga full-scale range. All sensor modules were sampled at $sf_S = 500$ Hz.

The sensors were positioned to measure motion of all limbs and segments relevant for the execution of a ski jump. The forearms for example were not exclusively captured, since the elbow joints in ski jumping are mostly rigid and the forearms moved in equal terms with the upper arms. In concrete, the following sensor positions were chosen: pelvis and both left and right thigh, shank, ski close to the tip of the ski boot and upper arm of the athletes (Figure 1). The sensors were securely placed directly on the athlete's body and ski using adhesive and kinesiology tape before the beginning of data acquisition.

Since the quality of a ski jump is defined by a mix of measurable jump properties (length, wind) and jury-based style assessment, we furthermore collected the jump length and style scores of every jump. Both measures were annotated on paper by an experienced ski jump judge in real-time and under real judging circumstances from the judge's tower. After data acquisition, all score sheets were digitized to serve as an indicator for the quality of a motion performance in the following.

Figure 1: Nine sensors were attached to the athlete's body and ski to capture the ski jumps.

3 DERIVATION OF BODY KINEMATICS

Despite the need for quantitative data, only a few studies addressed the use of inertial sensors for performance assessment in ski jumping so far (Ohgi et al., 2009; Lee et al., 2015; Bächlin et al., 2010; Chardonnens et al., 2012; Chardonnens et al., 2013). This is mainly due to the sparse raw data: inertial sensors measure acceleration, gravity and magnetic field information, which can generally not display all information necessary for a complete motion analysis. Simple characteristics and anomalies of a motion performance can be found from the raw data with statistical measures or spectral Fourier and wavelets filters. Body segment orientations and joint positions, as they can be obtained with other motion capture technologies, cannot be derived immediately and have to be computed in a post processing step. Various methods to determine significant information from inertial sensor data have been developed within the last decade (Madgwick et al., 2011; Euston et al., 2008; Yun and Bachmann, 2006). For the current study, we used an independent processing framework that we specially developed for the determination of full-body kinematics in ski jumping.

Starting with a raw data input, the processing framework consisted of the following sequence of computation steps: (1) determination of initial sensor orientations with an algorithm based on trigonometric relations in the field measurement vectors (Yun et al., 2008), (2) compensation of magnetic disturbances to correctly align every sensor to the global reference frame, (3) estimation of sensor orientation estimation by a Complementary Filter (Euston et al., 2008), (4) sensor-bone alignment to adhere for variations in the sensor placement and to determine body segment orientations, and (5) computation of relative joint positions with a forward kinematics approach using man-

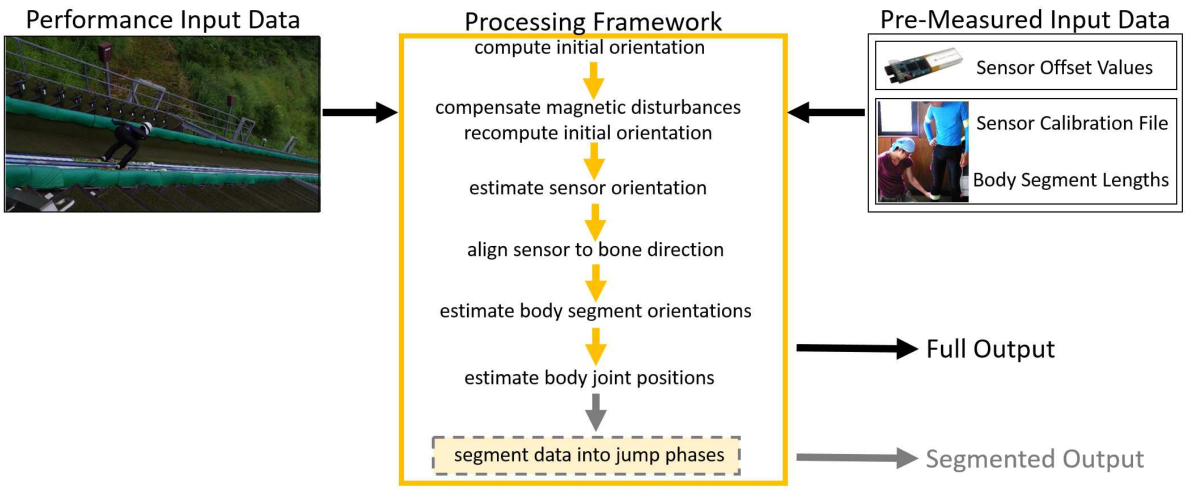

Figure 2: Schematic overview of the processing framework with initial attitude estimation, compensation of magnetic bias, sensor orientation estimation, sensor alignment and computation of the output body kinematics.

ually measured segment lengths. By the latter two steps, the system's output data in form of kinematic motion information was provided. Furthermore, we annotated the time instants of the two characteristic key-events take-off and landing on the base of the raw sensor data. Every data capture could then be segmented into its main motion phases in-run, flight and landing, which yielded an additional data output of phase-wise body kinematics (Figure 2).

The system accuracy has been successfully tested in a previous work, where it showed errors of $1-3$ degrees for the initial orientation estimates and drift errors of less than 5 degrees over the complete data capture respectively ski jump.

4 CREATION OF INTELLIGENT MOTION KNOWLEDGE

After the derivation of accurate and reliable kinematic motion information, the question was how to transform the obtained data into a meaningful description (respectively feedback information) of the performed motion. Similar to the complex knowledge of the human brain, which acquired the ability to perceive and understand motion performances during years of practice and experience, machine learning algorithms should be utilized to create an artificial intelligent motion understanding for this task.

4.1 Quality Measure

As a first step, it was necessary to determine a meaningful ground truth measure that could describe all relevant motion information and that could be used for the training of the machine knowledge. Criteria for style assessment are based on the biomechanical descriptions of the motion and are designed in such a way that they are universally valid and independent of an athlete's anthropometric properties. Good motion technique is generally also correlating to a higher flight curve and a longer jump. Therefore, we decided to use the collected style scores as a ground truth for this investigation.

According to the official scoring system specified by the International Ski Federation (FIS, 2013), marks are not given for good style, but deducted for faults. A perfect jump is awarded with a maximal style measure of 20 points per judge, and errors and deviations from the desired motion style in the motion phases flight, landing and outrun are fined by distracting points from the maximum score. Faulty behavior during the flight phase and the landing can be punished with a maximum point deduction of 5 marks each and during the outrun with a maximum point deduction of 7. On a fine scale, error points are deducted under the style criteria C shown in Table 1. They were used to annotate the collected ski jumps in the present work and correspond with the segmented jump phase of flight and landing.

4.2 Machine Learning

The applicability of the mobile training system depended largely on how well the processed inertial sensor data could describe a motion and especially depict all critical phases and properties that influenced its performance quality. Especially important here was to define meaningful feature representations that represented the structure and characteristic of the underlying data, and to chose and train a suitable machine

Table 1: Excerpt from official instructions on the judging of ski jump style. The presented performance errors per motion phase A (aerial phase) and L (landing phase) and their point deductions will serve as main style reference C in the following.

A	Aerial phase errors	max. 5.0
1	Insufficient control over body or skis during the formation of the stable and dynamic flight posture	0.5-2.0
2	Instability (unnecessary motion of the arms, uncontrolled body position, bent knees, not completely stretched legs)	0.5-1.0
3	Unsymmetrical positioning of the arms	0.5-1.0
4	Unsymmetrical positioning of the legs	0.5-1.0
5	Unsymmetrical positioning or unevenness of the skis	0.5-1.0
L	**Landing phase errors**	**max. 5.0**
1	No Telemark landing at all (feet parallel, single fault)	min.2.0
2	No smooth movement/transition from the flight pose to the landing	0.5-1.0
3	Slight Telemark landing, with little bending of the knees only	0.5-1.5
4	Insufficient absorption of the landing impact by the Telemark, or Telemark position is not maintained until the end of the landing process (instability, too stiff or not fully executed Telemark position)	0.5-1.5

learning method for the identification of style errors and faulty motion executions.

4.2.1 Motion Features

Research in activity recognition from wearable sensor data has resulted in a wide variety of possible feature transformations such as statistical raw-signal based features, event-based features, multilevel features derived from clustered statistical occurrences and kinematic body motion information (Bulling et al., 2014). Many processing methods used in the context of sports focus on low-level signal-based features and extract information directly from the raw sensor data (Milosevic and Farella, 2015; Dadashi et al., 2014; Ghasemzadeh and Jafari, 2011). In this study, we focused on body-model features described by positional and angular data or relations between body parts and body joints. The reason for this choice was that such 'motion property time-series' were closest related to the biomechanical description of the style criteria C. Besides, temporal execution of a motion as well as correct timing of key motion patterns are very important aspects of motor skill and the training of motor sequences.

For the following investigations, we designed a universal set of body-model features $\mathcal{F}_C$ that could also be used in similar applications for any other movement or sports data (Helten et al., 2011). In concrete, those features constituted the body kinematics obtained from the data processing framework (F_{C1} and F_{C2}), but also included further kinematic motion information built from angular and positional relations between certain segments and joints (F_{C3} and F_{C4}) (Table 2).

F_{C3} was computed from the angular information

Table 2: Description of the chosen (time-series) body model features $\mathcal{F}_C$ with their feature ID for the respective three sensor axes.

ID	Type	Description
F_{C1}	ϕ, θ, ψ	Roll, Pitch and Yaw in the global coordinate frame
F_{C2}	$x_{rel}, y_{rel}, z_{rel}$	Segment end (joint) position in the global x,y,z coordinate frame
F_{C3}	$\angle_{s1,s2}$	Angle between neighboring body segments $s1$ and $s2$
F_{C4}	$x_{j1,j2}, y_{j1,j2}, z_{j1,j2}$	Relative position differences of joints $j1$ and $j2$

of two spatially related, neighboring body segments and comprised the joint angles of highest influence on the aerodynamic effects of a ski jump: hip, knee, shoulder, ski elevation, ski opening and arm opening angle. For F_{C4}, the positional relations between right and left body parts (shoulder, hands, hip, feet, ski tips) along all three axes were used. Every feature was furthermore rescaled to the interval $[0,1]$. This rescaling standardized the feature range and made the features invariant to anthropometric differences (e.g. different body segment lengths) between athletes.

4.2.2 Error Classification Method

Conforming to the general style assessment of ski jumping, the basic idea for the creation of motion feedback information was to classify an input jump as either *error jump* (EJ) or *non-error jump* (NJ) with respect to all nine chosen style criteria. To address this problem, we chose a straight-forward implementation of the binary support vector machine (SVM). The principal idea then was to determine commonalities between two or more motion performances (meaning motion feature streams) of the same group EJ or NJ.

To handle temporal variations in the time-serial features, we added a data transformation based on a weighted-sum singular value decomposition before the main computation of the SVM (Li et al., 2005). This strategy can represent temporal information within a lower dimension as the concatenation of the projected first singular vector to the first principal component and the normalized singular value vector of the motion matrix. Closeness between two data streams is then registered if their resulting reduced feature vectors are of similar value, and difference if their vector elements are dissimilar. After feature transformation, the single feature vectors could be concatenated and used as input data for the SVM.

For the validation and evaluation of a machine learning system, it is common to have at least two different data sets: one used to learn the system and one used to test the trained system. To produce such a data base split within the 85 ski jump captures, we made use of the A and L phase-wise ground truth style annotations. For every C, the numbers of EJ and NJ jumps were determined and half of each jumps and their respective phase-annotated feature streams randomly assigned to the training data base. All remaining jumps were assigned to the testing database. To become more robust against random influences of the splitting process into training and testing database, we chose to use a k-fold cross validation (CV) with k= 2. This means that the classification was performed twice, whereas all data was used once for training and once for testing. To improve results, we furthermore added an internal 2-fold CV cycle for the training of the model parameters of the SVM to the main cycle, leading to a nested k-fold CV (Figure 3).

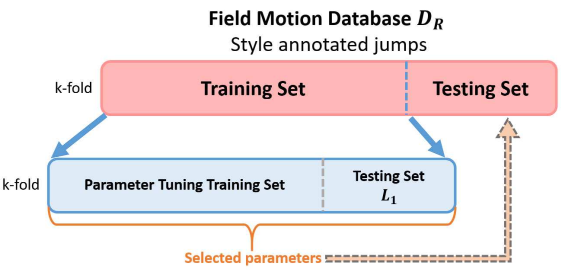

Figure 3: Schematic overview of the implemented nested cross-validation for the learning and validation of the intelligent machine knowledge.

5 RESULTS

As a measure for the classification accuracy we computed the precision and recall of the error annotation in the testing data, whereas the precision and recall values of both k-fold validation steps were averaged to yield a final output. Under the given problem, precision (P) was defined as the number of correctly classified errors n_{tp} divided by the number of all classified errors $n_{tp} + n_{fp}$. Recall (R) was defined as the number of correctly classified errors n_{tp} divided by the number of all elements that are actual errors $n_{tp} + n_{fn}$ for every C:

$$P = \frac{n_{tp}}{n_{tp} + n_{fp}}, R = \frac{n_{tp}}{n_{tp} + n_{fn}}. \tag{1}$$

Precision could hence be thought of as a measure of the classification's exactness, and recall as a measure of the classification's completeness.

In general, a low precision can indicate a large number of false positives n_{fp}, and a low recall many false negatives n_{fn}. Ideally, both measures should be close to 1 to show a good error recognition accuracy. Results of the nested CV showed that the implemented system was capable to retrieve errors of good accuracy in all style criteria C, and of high accuracy in most C, by either high P or R values (Figure 4).

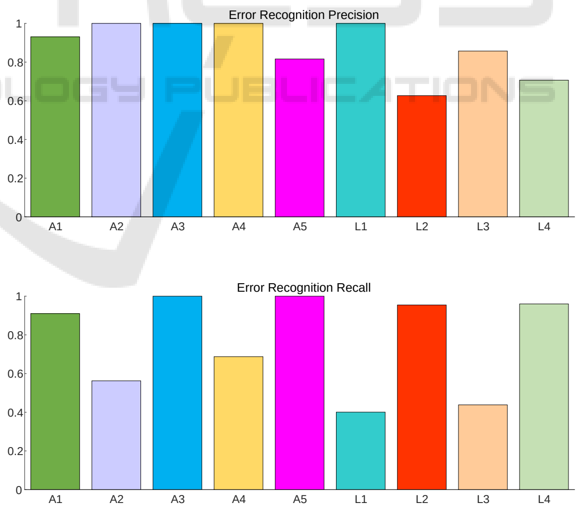

Figure 4: Precision and recall for the error recognition along all style criteria C. In a perfect retrieval, both metrics would be 1.

To obtain a combined accuracy measure representing all relevant classification statistics, we furthermore computed the normalized confusion matrices of all C (Figure 5). They contained the retrieval parameters n_{tp}, n_{fp}, n_{fn} and the number of true negatives n_{tn}, whereas a good classification was depicted by high

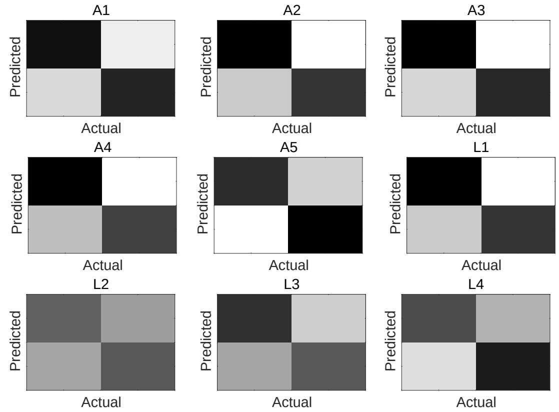

Figure 5: Confusion matrices for the error recognition along all style criteria C. The darker the color along the diagonal axis (first and fourth quadrant), the better the classification.

values along the diagonal axis (first and fourth quadrant) of the matrix:

n_{tp}	n_{fp}
n_{fn}	n_{tn}

In the present visualization, high values were denoted as black and low values (with a min value 0) as white.

Looking at the classification accuracy of every C, we realized that the features of precise error recognition were those features with clearly defined motion properties (e.g. $A2$, $A3$ and $A5$). Features of less accurate error recognition on the other hand were generally less specific with respect to their definition in the judging criteria (e.g. $L2$, $L3$, $L4$). One explanation here could be that such error annotations got interfused within the process of ground truth data acquisition, since their description was of similar semantic content. Further improvement of the results might therefore be achieved by a larger collection of training data for the classifier and more robust ground truth annotations. This could be achieved by simultaneously collecting style evaluations from several judges that would then be averaged and reduce the influence of misperception.

6 USE IN TRAINING SYSTEM

Knowing the accuracy of the system, the error recognition method should be used for the provision of motion feedback and style information to the athlete in the last step. The idea here was to implement a graphical user interface that can communicate with the athlete to give directed feedback on the motion (Figure 6).

In concrete, the design of the athlete-system communication should be as follows. First, incoming sensor data of a current motion performance is received, processed and classified under the style criteria C. Once the basic system computation is done, the athlete can ask for specific information on motion parts or motion properties by sending retrieval requests. Next, the respective information will be retrieved and delivered to the user.

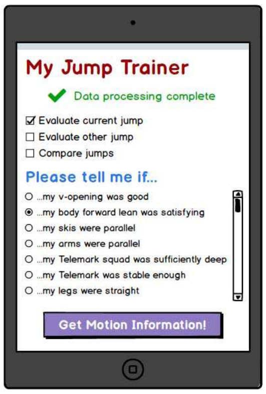

Figure 6: Sample implementation of a graphical user interface for the provision of directed feedback to the athlete.

Here, it is important to note that search criteria and keywords for communication with the training system were held general and intuitive by pre-defined search queries. Internally, those search queries were associated to one of the nine style criteria for information retrieval. A possible query in the user front end could for example be whether the arms have been held parallel during flight. In the back end this information would be labeled under the criteria $A3$, and the respective error recognition result for $A3$ could therefore be used to display an either positive (in case of NJ) or negative (in case of EJ) output feedback (Figure 7).

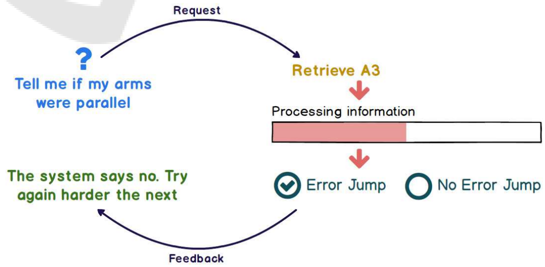

Figure 7: Sample overlook on the dialog between athlete and training system.

7 CONCLUSION AND OUTLOOK

In this work, we presented a novel approach for the provision of automatic motion feedback on the base of biomechanical style criteria for intermediate level ski jumping. First, motion performances were captured using nine inertial sensors. The inertial sensor data were then processed, so that relevant motion information and body kinematics were obtained. Next, a fundamental intelligent motion understanding defined by the guidelines for ski jump style assessment was built from the augmented motion data. This machine knowledge could then be used to provide motion feedback information to the athlete by simple pre-annotated search queries.

Validation of the underlying system methods showed that the system was capable to identify style differences and errors well. To enable a more specific training system for individual athletes, it might next be reasonable to use different quality measures independent of universal style criteria. This could for example mean to include numerical parameters known to influence a ski jump performance such as the body forward angle or the ski attack angle. Considering that the ideal flight style varies for every athlete in dependence on his or her individual anthropometrics and motor skills, it could furthermore be useful to build individual motion knowledge for every athlete. Data could then also be used to monitor the progression of skill over time. However, this would require a large data base of jumps per athlete before a meaningful motion knowledge could be created – something which is difficult to organize in practice.

The two biggest issues the system currently has to face are the provision of real-time feedback, as well as the correct handling and attachment of the motion sensors required for a future independent system use by athletes. Whereas the former can be addressed by the establishment of a wireless data network for data transmission at the ski jump hill, the latter is subject to the user. Consequently, possible sources of error should be held as small as possible. With the ongoing process of hardware enhancement, sensors would ideally be smaller and easier to use in future, such as for example by inclusion within the jump suit. To improve the system and verify its effect and usability, it is furthermore sensible to test the system under real conditions in near future.

All in all, we believe that the developed system is a very promising and powerful approach to the question of future motor training systems. We have shown that it is possible to provide and directly deliver motion information by learned machine knowledge. Especially in intermediate level sports – where the internal representation of a motor task is unstable and coaching feedback might be unavailable or incomplete – augmented motion information acquired by means of such mobile platform could considerably support correct motor skill acquisition. Ideally, it could enhance the training environment, and hence contribute to improved motor understanding, motor skill acquisition and safety.

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