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## Pattern recognition in cyclic and discrete skills performance from inertial measurement units

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### Abstract

The aim of this study is to compare and validate an Inertial Measurement Unit (IMU) relative to an optic system, and to propose methods for pattern recognition to capture behavioural dynamics during sport performance. IMU validation was conducted by comparing the motions of the two arms of a compass, which was equipped with IMUs and reflective landmarks detected by a multi-camera system. Spearman's rank correlation tests showed good correlations between the IMU and multi-camera system, especially when the angles were normalized. Bland-Altman plot, root mean square and the normalized pairwise variability index showed low differences between the two systems, confirming the good accuracy levels of the IMUs. Regarding pattern recognition, joint angle and limb orientation was respectively studied for 25 m during breaststroke swimming and 10 m of indoor rock climbing in athletes of various skill levels. Pattern recognition was also conducted on a macroscopic parameter that captured inter-limb coordination. IMUs revealed the potential to assess movement and coordination variability between and within individuals from joint angle measures in swimming and limb orientation time-series data in climbing.

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## 1. Introduction

Kinematic movement analysis is regularly conducted using 3D multi-camera systems recording a high number of spatial-temporal parameters of behaviour. Although video analysis of performance behaviours has displayed accuracy and functionality, the use of such multi-camera systems is highly time consuming and involves many steps that may contribute to increase measurement errors like system calibration and digitizing. Moreover, the use of a multi-camera system complicates analysis in ecological performance contexts and may prevent analysis of extended time-series data observed in cyclic activities. For instance, in swimming, 3D kinematical movement analysis traditionally used a multi-camera video device to film a calibration frame less than 30 m<sup>3</sup> in volume that limited data collection to two stroke cycles. A recent technological response to these challenges involved the design of small, wireless, light and wearable inertial measurement units (IMU) to collect continuous data from all cycles of an event. This kind of device usually combines one or more accelerometers, gyroscopes and/or a magnetometer to provide accurate 3D movement analysis. To be useful, IMUs must include functional portability (size, weight, wireless capacity), validity (in comparison to other systems like optic devices), high sensor accuracy, high measurement reliability, and appropriate sensor attachability to avoid disturbance through movement (Cuesta-Vargas et al., 2010). Such IMUs have been used for studying human posture and movement (Wong et al., 2007).

In cyclic activities, IMUs have been used to estimate walking speed (Yang & Li, 2012) and swimming speed and intra-cyclic variations (Dadashi et al., 2012). IMUs have also been used to identify swimming stroke phases (Dadashi et al., 2013). Understanding of the potential role of IMUs could be gained by analysing inter-limb coordination pattern variability during performance of complex multi-articular activities under varying task constraints. Indeed, investigations of complex dynamical movement systems have highlighted the potential functionality of coordination pattern variability as skilled individuals seek to continuously adapt to several interacting constraints (Davids et al., 2006; Seifert et al., 2013). Consequently, the aim of this study was twofold: (i) to compare and validate an IMU relative to an ubiquitous optic system for joint angle assessment, and (ii), to propose methods for joint angle and limb orientation pattern recognition to capture inter-limb coordination dynamics in sport.

## 2. Methods

### 2.1. IMU validation for joint angle assessment

#### 2.1.1. Protocol and data collection

After passively recording for 10s, a pilot movement consisted of a flexion-extension motion in 2D, using a compass with two arms of 0.4 m each, which were displaced by an operator in three conditions: (i) three trials of slow movements with different pauses leading to an angular plateau during reversal points and between flexions and extensions, (ii) three trials with slow movements without a pause, and (iii) three trials with rapid movements without a pause. Slow and rapid movements with the compass occurred for a period of five minutes, which allowed measurement of a minimum of 60 cycles. Three reflective landmarks were detected by a 21-camera system (Vicon®, Oxford Metrics, Oxford, UK) and were fixed at the extremity of each arm and at the centre of rotation of the compass. The two arms of a compass were also equipped with two IMUs that corresponded to a combination of a tri-axial accelerometer (+/-8G), tri-axial gyroscope (1600°/s) and a tri-axial magnetometer (*MotionPod*, Movea®, Grenoble, France). Data collected from the IMUs (with *MotionDevTool*, Movea®, Grenoble, France) were recorded with North magnetic references and could provide a Euler angle (i.e., yaw, pitch and roll), rotation matrix or quaternion (as explained by Sabatini, 2011). Both systems were used at a 100 Hz sample frequency and were synchronized and piloted with RTMaps (Intempora S.A., 2000), so that time-series were of similar duration.

#### 2.1.2. Data analysis

The absolute values and normalized values (in an interval [-1, +1]) of Euler angles were compared between recordings of the IMU ( $A_{sensors}$ ) and the Vicon system ( $A_{vicon}$ ), following two steps, as in previous work (Dadashi et al., 2012). In the first step, a Spearman's rank correlation was used to verify the association between the measurements derived from the two systems (with a level of significance set at  $p < .05$ ). Then, the agreement between the two systems in angle measurement was assessed by the use of a Bland-Altman plot, in particular the % spent out of the confident interval (Bland & Altman, 1986). In the second step, we investigated the mean accuracy of the sensors in measuring angles by using the normalized root mean squared measure (*NoRMS* in %) between angles from both measurement systems. Then, the normalized pairwise variability index (*nPVI*) (Sandnes & Jian, 2004) was also calculated as follows :

$$nPVI = 100\% \times \left[ \frac{\sum_{C_k=1}^N \left| \frac{A_{sensors} - A_{vicon}}{(A_{sensors} + A_{vicon})/2} \right|}{N} \right]$$

where  $C_k$  is the  $k$  measure realized by both materials, and  $N$  is the total number of measures.

## 2.2. Assessment of joint angle in cyclic skill and limb orientation in discrete skill

### 2.2.1. Protocol and data collection

The section exemplifies how the IMU could be used to assess joint angle during performance of a cyclic skill such as 40 cycles of breaststroke in a flume at 90% of maximal speed, as well as limb orientation in discrete skill performance, like 10m of indoor rock climbing at a route difficulty of 5c according to the French scale. In breaststroke swimming, participants were equipped with four IMUs (*MotionLog* which is an adapted version of *MotionPod* including a data logger with a waterproof design; Movea©, Grenoble, France). These were positioned on the left side of the swimmers: on the forearm (posterior surface of the proximal portion), the arm (posterior surface of the distal portion), the thigh (anterior surface of the distal portion) and the leg (anterior surface of the proximal portion), in order to place the sensors in direct contact with a bony part of the limb. The two limbs equipped with sensors wore strands of swimsuits in order to limit resistances due to the presence of the sensors. Prior to testing, the swimmers performed a vertical jump without flexing the leg to permit detection of simultaneous vertical acceleration in the four IMUs, for synchronisation purposes. In indoor rock climbing, participants were also equipped with four of the same IMUs positioned on the right and left climbing shoes and on the right and left forearms (posterior surface of the distal portion). The data from the IMUs were simultaneously collected with the *MotionDevTool* software (Movea©, Grenoble, France) from which rotation matrices were used to express the 3D orientation of limbs.

### 2.2.2. Data analysis

In breaststroke, the elbow and knee angles were respectively computed with *MoveaLab* software (Movea©, Grenoble, France) from the relative angles between the forearm and arm, and between the leg and thigh. These time series data were filtered with a low-pass Fourier filter (cut-off frequency 8 Hz) and cut cycle per cycle (i.e. one cycle beginning with a point of maximal knee flexion and finishing with the next point of maximal knee flexion). Pattern recognition was conducted on the continuous relative phase ( $\phi_{rel}$ ) between the upper and lower limbs in order to capture elbow and knee angle coupling (Seifert et al., 2011). Data on angular displacements and angular velocities were normalised at an interval [-1, +1] in as suggested by Hamill et al. (2000) and the elbow and knee phase angles were calculated. Finally,  $\phi_{rel}$  for a complete cycle was calculated as the difference between both phase angles, which allowed identification of different patterns of inter-limb coordination including in-phase ( $\phi_{rel} = 0^\circ$ ) and anti-phase ( $\phi_{rel} = +/-180^\circ$ ). The value of  $\phi_{rel}$  across the cycle indicates which oscillator globally leads the other (i.e., a positive value indicates that the knee is leading and a negative value indicates that elbow is leading

(for further details, Seifert et al., 2011). ANOVA with repeated measure compared time spent in in-phase pattern of coordination and standard deviation of continuous relative phase between expert and beginner.

In rock climbing, the limb orientation was assessed via a 3D vector derived from a rotation matrix. A pattern recognition algorithm was used to calculate the scalar product of one of the 17 possible vectors (Table 1) and the current vector. The higher the scalar product, the more aligned were the two vectors. The current vector is thus assigned to the closest pre-defined pattern. The 17 possible vectors were separated in three categories (forward, diagonal and lateral orientation). The nature of the inter-limb coordination was analysed through the difference between right and left limb vector. This angle difference was analysed by interval of 22.5°. Proportion of the 17 types of possible vectors for each limb and proportion of the eight intervals of 22.5° for right-left limb coordination was counted.

Table 1. Seventeen theoretical vectors of limb orientation identified by rotation matrix

		Rotation Matrix		
		X	Y	Z
FORWARD	Forward	0	0	1
	Oblique Down	-0.707	0	0.707
	Down	-1	0	0
	Oblique Up	0.707	0	0.707
	Up	1	0	0
DIAGONAL	Oblique Right	0	0.707	0.707
	Oblique Up Right	0.577	0.577	0.577
	Oblique Down Right	-0.577	0.577	0.577
	Oblique Left	0	-0.707	0.707
	Oblique Up Left	0.577	-0.577	0.577
	Oblique Down Left	-0.577	-0.577	0.577
LATERAL	Right	0	1	0
	Up Right	0.707	0.707	0
	Down Right	-0.707	0.707	0
	Left	0	-1	0
	Up Left	-0.707	-0.707	0
	Down Left	-0.707	0.707	0

### 3. Results

#### 3.1. IMU validation for joint angle assessment

Table 2 indicated an acceptable similarity level when angle values are compared between the two systems for slow motion of the compass with and without a pause. However, the accuracy of the IMU was lower during rapid motion, which was due to one sample with a drift at the beginning of the recording procedure. When the Euler angle values of IMU and Vicon are normalized in an interval [-1, +1], similarity between the two systems increased.

Table 2. Comparison of Euler angle between IMU and Vicon system

	Slow motion with pause	Slow motion without pause	Rapid motion
Angle difference (°)	4.9±1.3	5.3±0.4	8.6±9.7
% out of CI	2.1	1.5	4.1
coefficient of correlation (r)	0.99	0.99	0.99
NoRMS (%)	5.2	5.5	9.8
nPVI (% of mean value)	2.8	3.1	3.7

Table 3. Comparison of normalized angle between IMU and Vicon system

	Slow motion with pause	Slow motion without pause	Rapid motion
% out of CI	6.1	5.7	4.3
coefficient of correlation (r)	0.99	0.99	0.99
NoRMS (%)	0.02	0.01	0.02
nPVI (% of mean value)	3.7	3.8	5.4

#### 3.2. Assessment of joint angle in cyclic skill and limb orientation in discrete skill

Overall, pattern recognition aims to exhibit the nature and the variability of inter-limb coordination at the intra-cyclic, inter-cycle and inter-individual level. For instance, Figure 1 exhibits inter-individual comparison of knee and elbow angles and coupling within and between cycles in swimming. In particular, a higher percentage of

simultaneous knee and elbow flexion (and extension), reflecting an in-phase pattern of coordination, appeared in beginner than in expert (26.1% vs. 17.5% of the cycle duration spent in in-phase coupling). This finding signified lower variations of continuous relative phase values within a cycle for beginners (standard deviation of 34.1° vs. 66.3°).

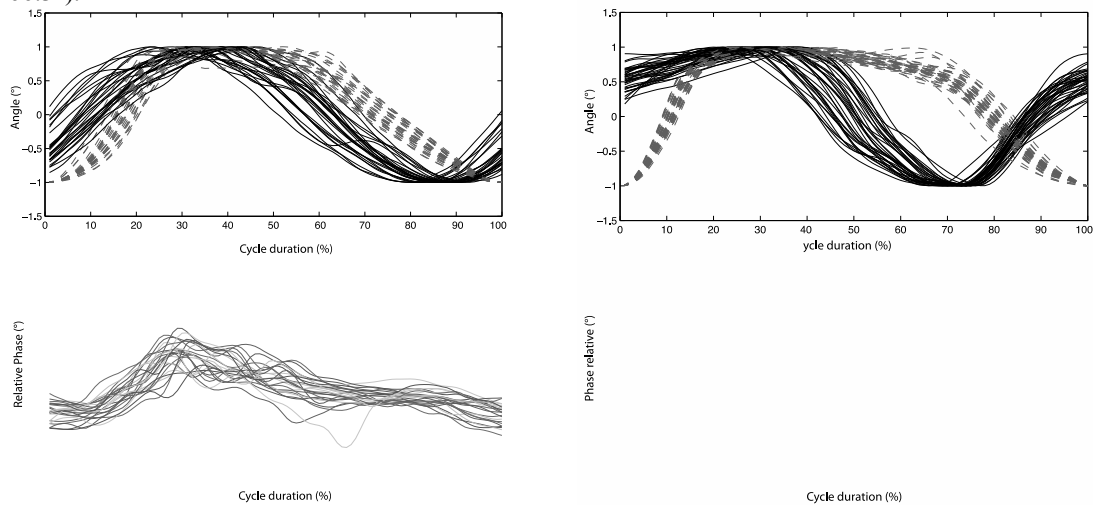


Figure 1. Example of knee (upper panel dashed line) and elbow (upper panel solid line) angles and continuous relative phase (lower panel) between knee and elbow for one beginner (left panel) and for one expert (right panel) for 40 cycles swim in a flume.

In indoor rock climbing, the pattern recognition in one expert climber highlights limb differences in the number and frequency of patterns through the ascent (Fig. 2). For instance, Figure 2 shows that the upper limbs are mostly orientated upward and obliquely upward. However, for both upper and lower limbs, almost all the 17 possible patterns seemed to be explored by the climber suggesting a large range of limb orientations. Right-left limb coordination is mainly in out-of-phase coupling (for instance, angle difference of 45°-67.5° represents a proportion of 25%) (Fig. 2).

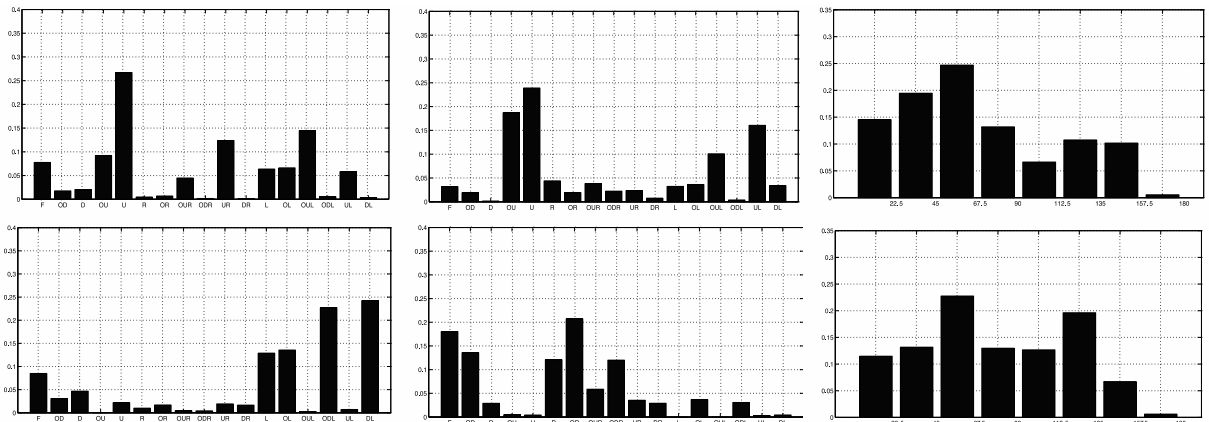


Figure 2. Proportion (in %) of 17 types of possible limb orientations for the right forearm (upper centre panel), the left forearm (upper left panel), the right foot (lower centre panel) and the left foot (lower left panel). F: Forward; OD: Oblique Down; D: Down; OU: Oblique Up; U: Up; R: Right; OR: Oblique Right; OUR: Oblique Up Right; ODR: Oblique Down Right; L: Left; OL: Oblique Left; OUL: Oblique Up Left; ODL: Oblique Down Left; UL: Up left; DL: Down Left. Proportion (in %) of eight intervals of angle difference (0-22.5°; 22.6-45°; 45.1-67.5°; 67.6-90°; 90.1-112.5°; 112.6-135°; 135.1-157.5°; 157.5-180°) for right-left forearm coordination (upper right panel) and for right-left foot coordination (lower right panel).

## 4. Discussion

### 4.1. IMU validation for joint angle assessment

When absolute values of Euler angles are compared between the two systems, the angle difference varied from 4.9 to 8.6°, with a higher level of accuracy in slower motions. In fact, the speed of the motion was not the main reason for the discrepancy between the two systems. Indeed, high standard deviations were found for rapid motions due to a drift of the IMU at the beginning of data recording. In particular, for one time-series the motion of the compass was initiated before 10s, which seemed to disturb the calibration of the IMU. This result indicated that a sufficiently long period of calibration was required before recording motion with the IMU. When this time-series is removed from the sample, the angle difference falls to a value of 5.2°. For clinical situations, Cuesta-Vargas et al. (2010) indicated that an error of 2° or less is considered acceptable. Errors between 2 and 5° are also likely to be regarded as reasonable but may require consideration in data interpretation. Our data revealed a mean error of 5°, mainly due to a drift relating to the IMU set-up, which only had a spatial, and not temporal, impact. This was because when the angle was normalized in an interval [-1, +1] cycle-to-cycle, the level of similarity between the IMU and Vicon system increased greatly. This finding suggested that, for cyclic skills like swimming where normalized angles are used to study inter-limb coordination, the IMUs appeared accurate.

### 4.2. Assessment of joint angle in cyclic skill and limb orientation in discrete skill

The use of IMUs to assess joint angles during inter-limb coordination in swimming and limb orientation in rock climbing provided an analysis of the range of movement and coordination patterns used over time. This technology allowed us to examine coordination in human movement systems, considered as complex, dynamical systems, permitting us to explore the functional and adaptive role played by coordination pattern variability within and between individuals. IMUs provide a promising platform to investigate how athletes cope with interacting task and environmental constraints during sport performance.

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