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Development of functional variability during the motor learning process of a complex cyclic movement

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Traditionally, movement variability is considered an indicator for sensorimotor malfunctioning. However, functional movement variability is also a result of compensation mechanisms e.g. to account for prior movement deviations and is, therefore, crucial for stable movements. The aim of this study was to analyze functional variability during motor learning of a complex cyclic task.

Thirteen young participants practised riding a Pedalo® slalom until they were able to complete the task without errors. Since trunk movements are controlled with high priority, we analyzed trunk kinematics as a result parameter. Since lower extremities affect the result parameter, foot, thigh and pelvis kinematics are considered execution parameters. The movement variability for result and execution parameters was determined for the first (poor performance), an intermediate (medium performance) and the last (good performance) training sessions. Furthermore, the variability ratio (execution/result parameter) was calculated as a measure of functional variability.

Movement variability of the result parameter decreased significantly with increasing expertise. In contrast, movement variability of all execution parameters increased significantly from measurements representing poor to medium performance. No change from medium to good performance was found. Functional variability increased over time in all execution parameters.

Since the movement variability of all execution parameters did not decrease with increasing Pedalo performance, applying a traditional interpretation approach of movement variability would have led to completely wrong conclusions. Possible mechanisms explaining the increased movement variability are discussed. The variability ratio seems to be the only parameter that can reveal improved sensorimotor functioning during all analyzed stages of motor learning.

1. Introduction

To evaluate sensorimotor control, cycle-to-cycle movement variability has been frequently quantified. In a traditional point of view, movement variability is an indicator for unwanted noise in the sensorimotor system (Davids et al., 2003; Schubert, 2013) and, thus, extreme levels of movement variability are interpreted as sensorimotor malfunctioning (Hamacher et al., 2016b; Singh et al., 2012). While this interpretation of movement variability is still frequently applied, we observe a paradigm shift. This paradigm shift is grounded on the fact that movement variability does not only depict malfunction in sensorimotor control but is also a result of adaptions to situational constraints or of mechanism to compensate for prior movement deviations (e.g. error) (Loosch, 1999). Especially in cases where small internal or external perturbations have to be overcome, the sensorimotor system must compensate those deviations in order to stay in a stable state (Müller et al., 2014). In those cases, compensation mechanisms would also result in movement variability. The latter types of variability are crucial for stable movement patterns in the ordinary case of small perturbations being present. Thus, we consider these types *functional* variability.

Such different aspects of movement variability have predominantly been addressed in acyclic movements, as in sprint starts (Bradshaw et al., 2007), pistol shooting (Scholz et al., 2000) and throwing movements (Müller and Loosch, 1999; Schorer et al., 2007). However, there are comparatively few studies analyzing functional variability of complex cyclic movements. One study, for example, observed that in gait the sum of variances in each lower extremity joint moment was higher than the support moment which was discussed as 'fine motor tuning' to 'correct minor deviations' (Winter, 1984, p. 60). Such corrections of minor deviations can be considered functional variability. For gait under varying conditions, movement variability was geometrically or

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statistically decomposed into its different parts (Papi et al., 2015; Qu, 2012; Tawy et al., 2018) and it has been suggested that functional variability may be phase-dependent (Hamacher et al., 2017). While most studies focused on kinematic measures, functional variability (covariation) was even verified for muscle torques (Park et al., 2016).

While the development of functional variability during motor learning of acyclic movements was already observed in a virtual throwing task (Cohen and Sternad, 2009; Müller and Sternad, 2004) and an arm reaching task (Müller and Sternad, 2003), there are, to the best of our knowledge, no studies evaluating functional variability in the process of motor learning of a complex cyclic movement task. However, as we will discuss, knowledge of the development of functional variability is fundamental to understand, analyze or interpret movement variability of complex cyclic movements, e.g. in gait.

To analyze different aspects of variability, approaches such as the Uncontrolled Manifold (UCM) (Scholz et al., 2000; Scholz and Schöner, 1999), the Goal Equivalent Manifold (GEM) (Cusumano and Cesari, 2006) or the TNC analysis (Tolerance, Noise, Covariation) (Müller and Sternad, 2003, 2004, 2009) were developed. We will (1) briefly explain the key idea of decomposing variability of those approaches by using a dart throwing task (acyclic task) as described by Müller and Sternad (2009). (2) Thereafter, the idea will be transferred to a cyclic task and (3) a more practical method of estimating functional variability for cyclic tasks will be deduced.

(1) To decompose variability, the effect of execution variables on a result parameter must be (biomechanically) modeled. In the dart throwing example, it makes sense to use the distance from the position of the dart to the target on the dartboard as an error measure. To quantify performance, the variability across multiple trials of this *result* parameter can be registered, which should be minimal. The goal can be reached by multiple combinations of execution parameter values: multiple different sets of initial dart velocities and initial angles at release can hit the target perfectly. Consequently, variability due to covariation (functional variability) might decrease the result parameter's variability, while random noise in the execution parameters would increase the variability of the results parameter. The UCM, GEM or TNC analyses use different analytical methods to calculate the effect of the execution on result parameters.

(2) In our study, functional variability of a cyclic movement should be analyzed. The task "riding a Pedalo®" was already chosen to analyze motor learning processes (Chen et al., 2005; Flôres et al., 2015; Totsika and Wulf, 2003). We choose *the Pedalo® slalom* since it is a quite challenging task to be learned by healthy young adults. To transfer the key idea of decomposing variability, we need to identify the result parameter. Since the HAT (head, arms, trunk) comprises about 2/3 of the body mass which has to be kept in balance in about 2/3 of the body height above the ground (Winter et al., 1990; Winter, 1995), the active trunk control with its large inertial load (Winter et al., 1990) is of outmost importance to enable dynamic stability during locomotion. Furthermore, the anticipated active top-down control of trunk muscles (Prince et al., 1994) attenuates accelerations from pelvis to head and provides a stable platform with regular and minimized head oscillations (Kavanagh et al., 2004; Kavanagh et al., 2005; Mazzà et al., 2008; Menz et al., 2003; Prince et al., 1994; Ratcliffe and Holt, 1997). This active trunk control is also discussed to improve visual and vestibular functioning (Pozzo et al., 1990; Prince et al., 1994). Thus, to analyse stability, trunk kinematics are frequently used (e.g. Bruijn et al., 2013; Hamacher et al., 2016a; Tamburini et al., 2018). Based on these findings on upright locomotion, the stabilization of the upper trunk is a parameter that is controlled with high priority. Therefore, we chose trunk movement variability as the results parameter of our pedalo task. As an execution parameter, e.g. the kinematics of the foot or the hip can be considered. The kinematics of the result parameter (trunk) might be stabilized by adjusting pedalo speed through altered foot movements or through altered hip angles (known as hip strategy). Again, noise as source of variability of the execution parameters would lead to increased variability of the trunk while covariation of execution parameters might decrease the trunk's variability. It is obvious that a complex motion analysis and a complex biomechanical modeling is a prerequisite for the UCM, GEM or TNC approach. While these approaches could result in more detailed findings, those are also very time-consuming for practical applications (e.g. gait analysis in clinical settings). Thus, we will deduce another approach based on the same key idea:

(3) We will use the fact that functional variability manifests as a relative low variability of the movement result parameter compared to the variability of execution parameters in the execution space. For example, due to covariation of execution parameters a relatively low variability of the result parameter can be achieved (Bootsma and van Wieringen, 1990; Müller and Loosch, 1999; Winter, 1984). Also, an anticipated or reactive (e.g. compensation for prior movement error) time-delayed compensation of execution parameters could stabilize the result parameter. We will use this relation and simply analyze the variability ratio of one execution parameter divided to the result parameter as a measure of functional variability. The effect of different sources of variability on the variability ratio is theoretically discussed in Table 1. While the absolute value of the

Table 1
The effect of different sources of variability according to the TNC analysis (Tolerance, Noise, Covariation) (Müller and Sternad, 2003, 2004, 2009) on the variability ratio.

Component of the TNC analysis	Brief description	Effect on the variability of the		Effect on the variability ratio
		Execution parameter	Result parameter	
Improved Tolerance	Finding a set of execution parameter values that are less sensitive to small perturbations	None	Less variability	Increased
Noise Reduction (random variability)	Less variance due to improved sensory-motor control	Less variability	Less variability	None (minor change)
Improved Covariation	Covariation of execution parameters to compensate for each other	None	Less variability	Increased
	Compensation e.g. in the case of small perturbations or to compensate for prior movement errors	Increased variability	None (or less increased due to covariation of execution parameters)	Increased

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