2016 14th International Conference on Control, Automation, Robotics & Vision
Phuket, Thailand, 13-15th November 2016 (ICARCV 2016)

Quantifying Task Similarity for Skill Generalisation in the Context of Human Motor Control

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***Abstract*—In this work, a simple model is used to characterize the learning behaviour of humans. Based on this model, it is possible to define a similarity measure between two tasks in order to quantify skill generalisation during the learning of simple motor tasks by humans. By fully exploring this similarity measure, a sequence of tasks capable of improving the learning efficiency for both healthy subjects and patients with motor impairment may be generated. A validation protocol is introduced and preliminary experimental results with six subjects are presented to validate the learning model and the similarity measure. Results show that the human learning of trajectory tracking tasks can accurately be modelled by an exponential decay of the average tracking error. The model fits well when the task is new or far away from a previously learnt task. Model parameters are used to analyse the learning performances of the subjects and the influence of previous tasks learning. Finally, it is shown that the similarity index can be constructed based on the proposed model to reflect skill generalisation.**

I. Introduction

Skill generalisation is an important process in the development of human motor control, specifically in the expansion of the repertoire of motor skills. In the development of new motor skills, humans build on a library of established skills through this generalisation process. Computational modelling of generalisation can be used to improve the conventional models of motor learning and control, and understand the relative complexity of motor tasks. This knowledge can potentially be utilised in several applications, such as to improve the training regime for athletes, improving the learning of precision manipulation skills or even the planning of effective motor rehabilitation treatment.

The work reported in this paper is primarily motivated by the application of robot-assisted rehabilitation of motor impairment. In this application, a patient with neuromotor impairment (such as a stroke survivor) undergoes physical therapies consisting of exercises in order to regain the motor skills lost due to the trauma. Robotic assistance has been identified as having significant potential in this exercise, when used in conjunction with supervision from clinical experts [1]. In the development of these robotic devices, in addition to the physical assistance that has been much studied recently, it is also important to design the exercises such that the difficulty is suitable for the stage of recovery and/or the set of motor capabilities of the patient [2]. A systematic framework for defining or assigning these exercises would be ideal for implementation on a robotic rehabilitation system, due to its quantifiable and logical nature, and would provide significant potential in assisting clinicians in their tasks. Specifically, it would be advantageous to be able to assign exercises which are both not too close to, but also not too far from previously completed exercises, to fully motivate the movements of the patient, leading to a possible improvement in the recovery rate. Therefore, an understanding of how motor skills generalise from a task that is learnt, to another (new) task that is "nearby" is needed. In this paper, we report our initial findings, in the endeavour to quantify the "similarity" between tasks in the context of human motor control.

Task generalisation is an established approach in the clinical fields such as in physiotherapy. In these fields, intense or focused exercises are then followed by application of the learnt skill to a set of variations of task setting. Despite the importance of the generalisation process in human motor control, the study of human motor learning is often limited to a given task or to the reaction/adaptation of the human to a change of the environment, either kinematic (e.g. a change of the visuomotor transformation [3]–[6]) or dynamic (e.g. a change in a force field perturbation [7]–[9]), but with a focus on modelling the transient and the washout —or after-effect— more than the actual re-utilisation of previously acquired skills. In robot assisted rehabilitation therapy, the subject is exposed to a sequence of exercises. It is intended that this sequence favour a progressive re-learning of skills. In this perspective, this work is a preliminary case study to investigate the effect of intermediate tasks in the successive learning of tasks in healthy subjects.

Examples of studies on the learning of successive motor tasks and the associated skills transfer can be found in literature. These studies can be classified into three modes of generalisation:

- Performing a task with one body segment (e.g. elbow) influences the subject's ability to perform the same task with another segment (e.g. shoulder) either in a positive way: *transfer* or a negative way: *interference* [10], [11].
- The ability to perform a task with the dominant arm can transfer to the non-dominant arm in some conditions, mostly depending on the subject's degree of handedness [12]–[14].
- The transfer of the learning of one task [15], [16], or a set of tasks [17], to the learning process of another *relevant* task has also been demonstrated in various degrees. Additionally, a negative *interference* has also been observed when the two tasks are clearly in opposition [18].

The body of work in the third category represents the most relevant background to the work in this paper. Within this category, it is suggested that the similarity between two

978-1-5090-3549-6/16/$31.00

different tasks plays an important role in the transfer process. Nevertheless no systematic quantification of the similarity between two tasks has been reported, to the best of the authors' knowledge. Thus no conclusion has been drawn on how this similarity influences the transfer of motor skills. It is the intention of this paper to establish a measure to quantify the effects of previous learning on the characteristics of a new motor task acquisition process. Ideally, this "measure" will be able to capture the generalisation of motor tasks based on the *similarity* between the tasks involved.

It is important to note that there is no one unique definition of *similarity* between two tasks, even for a specific subset of tasks. Motion based tasks can be thought of as being similar based on the construction of the motion, such as the components of the muscle groups or motor primitives [19], [20] used in generating the motion, or even the spatial and temporal components of the prescribed motion (such as the frequency domain components that constitute the prescribed trajectory). However, in this work, we define task similarity between tasks A and B as the effect that learning Task A before Task B has on the motor performance (in execution and learning) of Task B. That is, two tasks are considered similar if learning one task assists in the learning of the other. This is based on the fact that the nervous system may transfer some learning between tasks that share some characteristics [21]. This definition thus means that any computational model generated must be compared empirically against subjects' behaviours.

As our focus relates directly to the generation of motion, specifically using the upper limb, we focus the study on the learning of trajectory tracking tasks using one's hand, where the participant tries to closely follow a reference trajectory defined on a 2D plane [22]–[25]. The tasks are carried out by having subjects holding onto the end effector of a planar robot to perform the prescribed trajectories associated with each task. Three distinct tasks are defined and two groups of subjects were instructed to learn these tasks in different sequences. The effect of the previously learnt task on the learning dynamics of the next task was investigated.

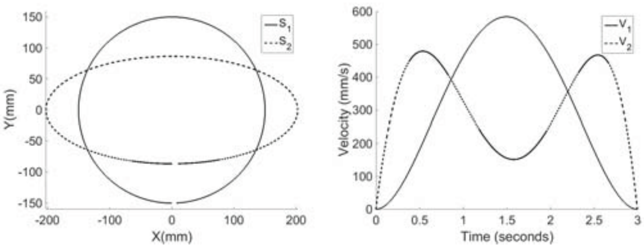
II. Task Definition and Learning Analysis

The aim of this study is to investigate measures for defining task similarity, based on how the process of learning a new motor task benefits from having learnt a previous task. This section explains the hypothesis to be tested in this case study, the set of tasks considered for the evaluation of successive learning, the experimental set-up, and the methods of analysis. A simple model of learning is used to identify the key characteristics of the learning process for a given subject and a given task. The effect of learning an intermediate task is then observed through the identified learning characteristics. Finally, the same model is extended and used to directly represent the successive learning of several tasks and to observe the relation between two different successive tasks in terms of motor learning capabilities.

A. Task Definition

In trajectory tracking tasks, the participant is instructed to closely follow a moving target along a predefined path with a predefined velocity profile. Three planar tracking tasks have been designed for this experimental case study. The tasks were 2D continuous trajectories and the performance of the task was defined as the error in tracking this trajectory. Learning is then the process of improving the performance over multiple attempts of the task in the presence of feedback, which was presented as an error dependant score at the completion of each trial. The task trajectories were designed to be sufficiently fast to prevent subjects from relying on their visual feedback and instead having to perform them through feed-forward control [26]. Thus, during this process, it is assumed that the subjects develop and tune an internal feed forward representation of the task, thus "learn" the task.

The first task (T_1) consists of a circular path (S_1) in space with a bell shaped velocity profile (V_1) [27]. The second task (T_2) is an elliptical path (S_2) with the same velocity profile, V_1. Finally, the third task (T_3) is the elliptical shape (S_2) with a double bell shaped velocity (V_2) to differentiate velocity profiles. The two shapes and velocity profiles are shown in Fig. 1. Instead of designing the velocity profile in Cartesian coordinates, the path is parametrised to obtain the tangential velocity (see Figure 1 (b)) which can be used for different shapes, for example (T_1 and T_2). Moreover, the circumference of both shapes are equal, and velocity profiles are designed such that the total duration of each trajectory is equal for all three tasks.



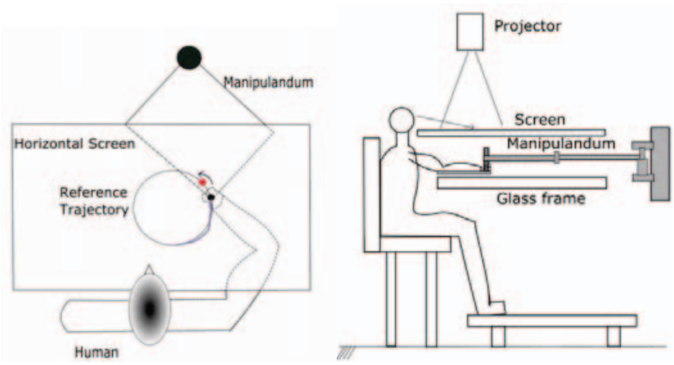
(a) Shapes (b) Tangential Velocities

Fig. 1: (a) Shapes in XY coordinates and (b) tangential velocity profiles, used to define the different tasks.

B. Experimental Set-up and Protocol

Experiments were conducted with six healthy subjects (5-Male,1-Female, 24-30 year) using the subject's dominant hand. Each participant was informed of the protocol, the goal of the task and the meaning of the feedbacks before starting the first trial. The protocol was approved by the Human Research Ethics committee of The University of Melbourne (ID: 1545854.1).

The experimental set-up consisted of a manipulandum placed on a horizontal smooth glass platform and a virtual interface projected onto opaque white screen above the glass platform, between the subjects' eyes and the manipulandum. The interface displayed the task trajectory, score, and other feedback (such as timing) to the subject. The subjects sat on a chair in upright position and held the end effector of manipulandum through a support structure for the forearm.



(a) TOP VIEW (b) SIDE VIEW

Fig. 2: Schematic of the experimental setup

Pneumatic suspension was provided at the support structure to ensure smooth motion over the glass platform.

The shape of the trajectory to be learned was displayed on the screen and the position of the manipulandum handle was directly mapped to the position of a black dot cursor on the screen. An experimental trial started from a home position on the task's path. Subjects initiated the movement by moving out of the home position, after which a red dot begun moving along the task trajectory at the task's velocity. The subject was asked to closely follow the red cursor along the given trajectory. A schematic of a human subject performing a trajectory tracking is shown in Fig. 2. At the end of each trial the performance score was provided to the subject to provide motivation and a self evaluation of their performance. Participants were also able to see their own path superimposed on the required path. The reported score was inversely proportional to the average error of each trial. The trajectory data was recorded for n points at 500Hz. The average task execution error of the i^{th} trial, $e_{av}(i)$ was calculated as:

$$e_{av}(i) = \frac{1}{n}\sum_{j=1}^{n}\sqrt{\left(x_{h,j}(i) - x_{t,j}\right)^2 + \left(y_{h,j}(i) - y_{t,j}\right)^2}, \quad (1)$$

where $(x_{h,j}(i), y_{h,j}(i))$ denotes the position the trajectory tracked by human for the i^{th} trial and $(x_{t,j}, y_{t,j})$ corresponds to the position of the target trajectory (iteration-invariant). The score for each trial is computed as

$$e_s(i) = \frac{2}{e_{av}(i)}, \qquad , i = 1, 2, \ldots . \quad (2)$$

This indicates that subject has to learn the task by improving the score. A moving average of window size 5 is used as a part of stopping criteria:

$$\hat{e}_{av}(i) = \frac{1}{\min\{5, i\}}\sum_{j=i-4}^{i} e_{av}(j), \forall i = 1, 2, \ldots, \quad (3)$$

where $e_{av}(j) = 0$ for any $j \le 0$. The experiment continued until the subject succeeded in achieving an $\hat{e}_{av}(i)$ less than a predefined success threshold ($\epsilon_s = 0.012m$ or $12mm$) or the trials reaches a maximum limit ($N = 180$). This stopping condition was constructed to ensure that the subject either had learnt the task, or had reached a steady state where a further improvement was unlikely.

Participants were randomly assigned to two groups. Group-1 participants were asked to successively learn tasks T_1, T_2 and T_3 and Group-2 participants were asked to successively learn tasks T_1 and T_3. Task T_1 acts as a baseline task for a common evaluation of subject's capability in learning a trajectory-based task while T_2 serves as an intermediate step between T_1 and T_3 for subjects in Group-1.

In order to mitigate the effects of fatigue, short breaks of 5 minutes were allowed at the end of each task and participants were allowed to take a few minutes break every 100 trials.

C. Methods of Analysis

1) Learning Model: An exponential function was used to model the evolution of the tracking error measured over the training trials. Although several different mathematical models, such as S-shaped [28] or power laws [29] have been proposed to represent human motor learning, exponential functions are the most common [30]–[33]. Nevertheless no example of analysis of the learning process of trajectory tracking tasks was found in literature. The choice of an exponential decay function to model the learning over iterations has thus been driven by observation of the learning profiles and existing literature.

The trajectory of hand movement during each trial i is analysed to extract the task execution error $e_{av}(i)$ (see Equation (1)). In order to remove the outliers from fatigue or not focusing, trials where the subjects did not fully attempt to perform the task — as defined by a hand movement not crossing the middle line of the task — were excluded in the analysis. The evolution of this performance index was then modelled as:

$$e_{av}(i) = a\exp^{-bi} + c, \qquad i = 1, 2, \ldots, \quad (4)$$

where a, b and c are positive constants that to be identified from experimental data. In this model (4),

1) the constant c correlates to the steady-state error in the iteration domain;
2) the constant b defines the subject learning rate for the given task;
3) the sum of two constants $a+c$ represents the initial error of the subject for the task.

It is proposed that such a simple model is able to characterize a subject's learning process, allowing analysis of the effect of learning previous tasks on future tasks. Comparison of rates b and initial errors $a + c$ across subjects as well as between groups are thus performed to investigate this effect.

Two variations of the model were considered, both following the exponential decay function (4). In Case-1, the equation (4) is fit to error for each trial. In Case-2, the model is fit on the error filtered using a moving average filter of window size 5. That is, the filter produces a moving average $\hat{e}_{av}(i)$ from the information of the last five trials (see Equation (3)). Case-2 was included as it more accurately represents the exact instructions given to the subjects in terms of stopping criteria.

The function *fit* from MATLAB software (MATLAB and Statistics Toolbox Release R2014b,The MathWorks Inc, MA) was used to fit the equation (4) to the performance index. The coefficients (a, b, c) were calculated with 95% confidence bounds. The goodness of all the fittings were evaluated using the coefficient of determination, R^2.

2) Successive Learning of Tasks: What we proposed in this paper is the hypothesis that the learning of the intermediate task (T_2), between the learning of (T_1) and (T_3), influences the learning of (T_3). Intuitively, if two tasks are similar, the concatenation of the two curves representing the learning process of the two tasks will approximate a single learning process. The extreme case of this hypothesis is constituted by considering two successive learning processes of the same task: the obtained learning curve will be reduced to a single learning process that can be modelled by (4). In order to verify this hypothesis, these parameters are compared between Group-1 and Group-2 for each task.

In this work, a similarity coefficient s_{xy} is defined for two tasks T_x ($\hat{e}_{av,x}(i)$, (a_x, b_x, c_x)) and T_y ($\hat{e}_{av,y}(i)$, (a_y, b_y, c_y)). Task T_x is finished in N_x^{th} iteration. A combined task $T_{xy}(i)$ is characterized by ($e_{av,xy}(i)$, a_x, b_x, c_x)) is used. That is, in T_{xy}, T_y is treated as a continuous learning from the T_x. More precisely, the similarity of T_y to T_x can be captured by $\left(a_x e^{-b_x N_x} + c_x\right) e^{-b_x(i+N_x)} + c_x$: where this model fits sufficiently good if T_y is a continuous learning from T_x. A similarity coefficient s_{xy} is then introduced as:

$$s_{xy} = \frac{var\left(\hat{e}_{av,y}(i) - \left(a_y e^{-b_y i} + c_y\right)\right)}{var\left(\left(\hat{e}_{av,y}(i) - \left(a_x e^{-b_x N_x} + c_x\right) e^{-b_x(i+N_x)} + c_x\right)\right)} \quad (5)$$

where var represents the statistical variance. This similarity coefficient is used to evaluate successive learnings of (T_1) (T_2) (noted $[T_1T_2]$), (T_2) (T_3) (noted $[T_2T_3]$) and (T_1) (T_3) (noted $[T_1T_3]$).

The similarity of the tasks is thus reflected by the fact that two consecutive learning processes can be modelled as a single one. Comparison of similarity coefficients between the two groups and the different tasks are performed.

III. Results and Discussion

The number of iterations performed by all subjects for all tasks are tabulated in Table I. In Group-I, only one subject managed to achieve the desired tracking performance($\hat{e}_{av}i$ is less than the threshold) for all tasks (T_1,T_2,T_3), resulting in the stopping condition. A second subject reached the success threshold for task T_3 only. In Group-II, no subjects reached the desired threshold before the maximal number of iterations ($N = 180$). Despite this, the decay of the tracking error for all subjects during the training can be clearly observed (see Figure 3 as an example).

TABLE I: Number of iterations to learn the task

	Tasks	Group-1			Group-2		
		Subjects			Subjects		
		1	2	3	4	5	6
Trials	T_1	45	180	180	180	180	180
	T_2	148	180	180	N/A	N/A	N/A
	T_3	87	180	164	180	180	180

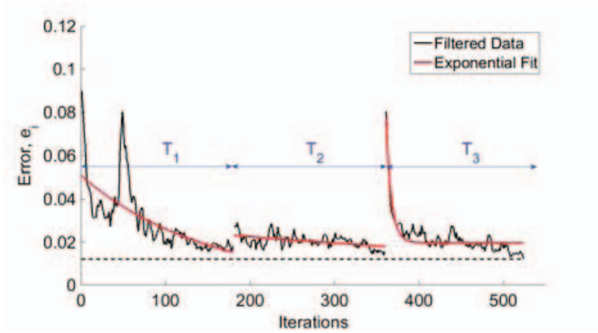


Fig. 3: The evolution of error for all tasks performed by Subject-3 from Group-1.

A. Learning Model

The exponential learning model (4) was fit to the task execution error (calculated using equation (1)) for all the tasks performed by subjects from both groups. Fig. 4 presents a representative example of the error evolution and the associated models for both Case-1 (trial-by-trial error) and Case-2 (moving average error) for Subject 6, T_1. The coefficient of determination of the model for both cases (as defined in Section II-C1), of all tasks and all subjects are presented in Fig. 5 and in Table II.

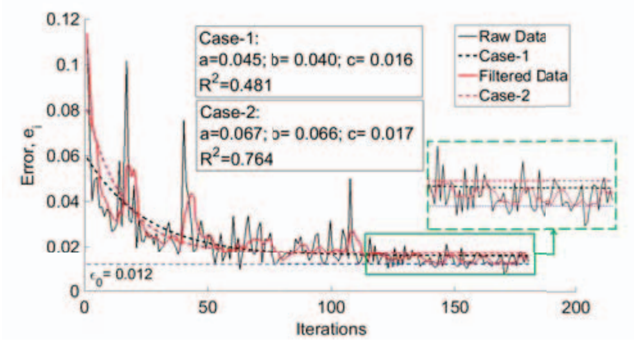


Fig. 4: Curve fitting : Subject-6, Task,T_1

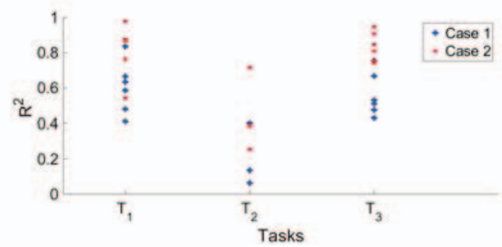


Fig. 5: R^2 values for Case-1 and Case-2

It can be observed that the model can represent the learning process of the tracking tasks for all subjects in T_1 and T_3 with a minimal R^2 coefficient of 0.41 for Case-1 and 0.54 for Case-2. This confirms that trajectory tracking tasks' learnings can be modelled by a simple exponential decay function with an appropriate error measure.

Nevertheless, it is interesting to note that the learning of T_2 is clearly less well represented by the model than the other task. As can be seen in Fig. 3, the error evolution for this task

TABLE II: The coefficient of determination,R^2

Subject	R^2					
	Case-1			**Case-2**		
	T_1	T_2	T_3	T_1	T_2	T_3
Subject 1	0.835	0.136	0.668	0.978	0.387	0.945
Subject-2	0.632	0.399	0.753	0.875	0.714	0.909
Subject-3	0.409	0.063	0.474	0.542	0.254	0.845
Subject-4	0.665	N/A	0.512	0.866	N/A	0.751
Subject-5	0.585	N/A	0.429	0.872	N/A	0.741
Subject-6	0.481	N/A	0.530	0.764	N/A	0.810

appears to not follow an exponential decay but is closer to a slow, linear reduction. This can be explained by the similarity of T_2 to T_1, leading the learning process of T_2 to be assimilated to a natural continuation of the learning of T_1 by the subjects and thus appears to be closer to the "tail" of an exponential decay. This is this effect which is intended to be modelled in Section III-C.

As expected the modelling of the moving averaged error, Case-2, performs better than the modelling of the trial-by-trial error, Case-1, mainly because the variability of the data is reduced and also possibly because this directly reflects the task instructions given to the subjects.

B. Learning parameters

In this analysis, we wish to observe whether learning T_2 prior to T_3 (Group-1) influences the learning of T_3 compared to learning T_3 without learning T_2 (Group-2). The evaluation of learning is based on the parameters extracted from the modelling performed in Case-2.

In Fig. 6 it can be observed that the $a+c$ value, representing the initial error state of the subjects at the beginning of each training is evenly distributed across groups, with a large spread for T_1 but with a significantly reduced spread at the beginning of the training of T_3. This indicates that the initial common training of T_1 acts as a normalization process for the subjects who reached a "common" baseline, as expected. It also suggests that the intermediate training of T_2 does not affect the initial performance of T_3. It is also observed that the initial state for T_2 is clearly lower reflecting how T_2 is similar to T_1 —differing only slightly in shape—, as already reflected by the limited fitting quality of T_2.

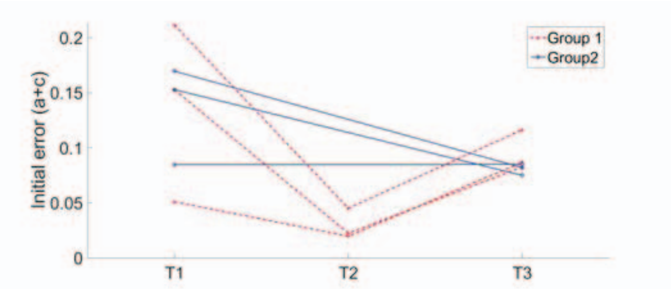


Fig. 6: Initial error of all tasks T_1,T_2 and T_3

Fig. 7 compares the learning rate b, reflecting how fast a subject learns a task. As the learning rates for T_3 are similar, it appears again that the training of T_2, does not produce a real benefit. It is to note that subjects with the slower learning rate in T_1 seemed to benefit more from the training (either in Group-1 or Group-2). Nevertheless, the limited number of subjects coupled with the inherent human variability does not allow a clear conclusion to be drawn. Furthermore, T_2 with a b coefficient appears lower, in coherence with its poor modelling as an exponential decay.

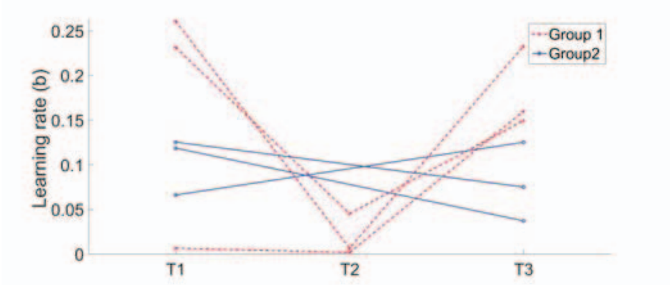


Fig. 7: Learning rate of all tasks

Similarly, the steady-state value c (Fig. 8) and its evolution for Group-1 and Group-2 does not show any significant difference between the two groups. However, the trend does suggest that the intermediate learning appears to be beneficial to the final performance achieved by the subjects (lower c value) despite the potential fatigue for subjects in this group —who were trained on one additional task.

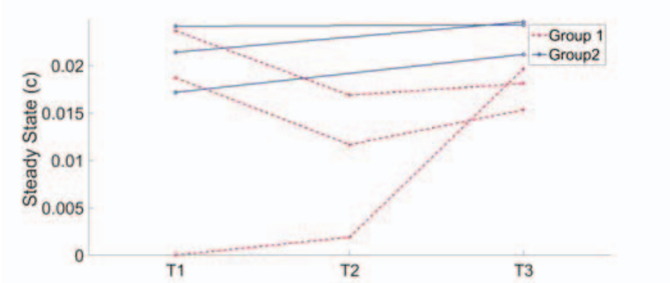


Fig. 8: Steady state value of error

C. Successive learning modelling

The similarity indices are calculated by considering dual task learning ($[T_1T_2]$, $[T_2T_3]$ and $[T_1T_3]$) as a single learning process (as described by Eq. 5). The values for these indices are reported in Table III. In this measure, the higher the similarity index, the greater the similarity between the tasks.

TABLE III: Similarity index

Similarity Index (s_{xy})	**Subjects**					
	1	2	3	4	5	6
s_{12}	0.698	0.133	0.618	N/A		
s_{23}	0.329	0.296	0.368			
s_{13}	0.289	0.297	0.516	0.288	0.319	0.316

For Group-1, the similarity index between task T_1 and T_2 for Subjects 1 and 3 are two times higher than for any other combination of tasks. This confirms that the successive learning of T_1 and T_2 is close to a continuous learning, and thus that tasks T_1 can be considered closer to T_2 than to T_3 or than T_2 to T_3. However, for Subject 2, the similarity index is comparatively less. This can also be observed in the data for Subject 2 by the prominent exponential decay in the learning of task T_2 rather than continuous learning from task T_1. This suggests that this task proximity measure is not necessarily shared by all subjects and/or that external factors —such as concentration, fatigue or surprise— can have a relatively high importance on the learning process. However, the intermediate learning of T_2 does not affect the similarity of T_1 to T_3 — as shown by comparable similarity indexes s_{13} for both groups. Interestingly, this suggests that the proposed similarity metric is not necessarily restricted in evaluating the proximity of two tasks learned directly successively.

IV. Conclusions and Future Work

This case study investigated the learning behaviours in the successive learning of trajectory tracking. The human motor learning of trajectory tracking tasks is modelled using an exponential decay of performance index and is used to assess the effect of successive learning of tasks. It is observed that the exponential decay of the error is more prominent if the learning task is not very similar to previously learnt tasks. A quantifiable measure to model task similarity is proposed based on a joint modelling of two learning processes. It is also observed that differences in the tasks' velocity profiles seems to play are more important role in the learning process than the difference in shape. Future investigation involving more subjects in order to reduce the inherent effect of human variability remain necessary to confirm the validity of the proposed method.

Acknowledgment

This study is supported by the ARC Discovery Project DP160104018.

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