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Model development and supporting data

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Summary

One of the most common instruction-strategies for training complex skills is part-training. A complex task can often be divided into part-tasks. Part-training requires that certain part-tasks or combinations of part-tasks be practised in isolation in order to promote the transfer of skills that are needed to perform the whole task.

In this paper a model is developed for the optimisation of schedules for part-training. The model is based on individual learning, but may be generalised to groups of trainees. It is based on the idea that if there is functional skill transfer from part-training to whole-task performance, then there must be a training schedule that yields optimal results. In this context, an optimal training schedule is one in which part-training lasts as long as is necessary to ensure the best possible performance with the whole-task at the end of the training.
To prove that an optimal training schedule does in fact exist, an experiment was conducted in which two groups of trainees received sixteen hours of training to learn a complex vehicle control task. One group received whole-task training only, the other group received training with one part-task before being transferred to the whole task. The individual skill-level of all trainees was measured repeatedly by recording the times needed to successfully complete trials on the whole task.

From an analysis of the individual learning curves a ‘skill transfer function’ could be identified. This function was used to determine the optimal part-task schedule. Practical applications of the ‘optimal transfer model’ are discussed.

Contents

(22 pages in total)

1 Introduction

Dividing the whole-task into part-tasks

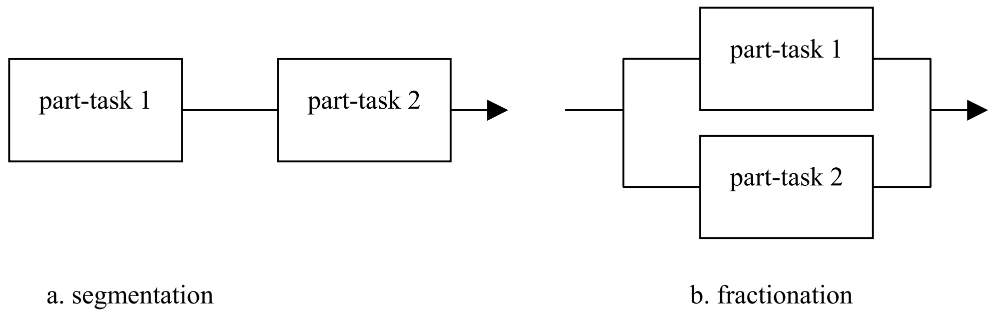
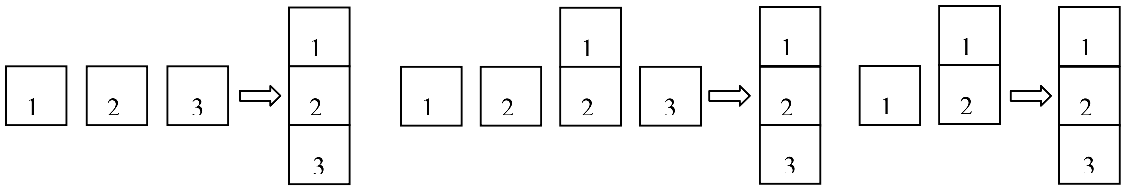


Figure 1: Serial and parallel execution of part-tasks

Part-training (or part-task training) has been defined as the training of a number of separate components (part-tasks) as the precursor of practising the whole task. The basic principles of part-training are twofold: (1) the separation of the whole task into part-tasks and (2) the scheme for integration of the part-tasks during training. According to Wightman & Lintern (1985) the whole task can be divided into part-tasks in three basic ways: (1) segmentation, (2) fractionation and (3) simplification.

When the task is divided along spatial or temporal dimensions, the division is called segmentation (figure 1a). This method applies when task components have a clear beginning and end in space or time, i.e. when different task components are executed serially in the whole task. An example from aviation is the handling of the Control and Display Unit (CDU), which can be considered to be a segment of the whole flight task. Other examples are in-line parking of a car or joining the traffic when you drive onto the motorway, both of which can be considered as segments of the whole driving task. Fractionation (figure 1b) applies when different task-components can be executed in parallel in the whole task. For example, the control of pitch, roll and yaw channels in co-ordinated aircraft manoeuvres can be considered as separate fractions, or checking the rear-view mirror in a car manoeuvre can be considered as a fraction. Finally, simplification applies when part-tasks are the result of the modification of features of the whole task. An example is the reduction that is made in the number of aircraft per unit time entering the controlled airspace in a simulated air traffic control task.

Re-integration of part-tasks during training



a. pure part-training b. progressive part-training c. cumulative part-training

Figure 2: Integration of part-tasks

Reconstruction of the whole task from its part-tasks in the course of the training can proceed according to different schemes (figure 2). The basic schemes for task integration are (1) pure part-training, (2) progressive part-training and (3) cumulative part-training. In pure part-training, all part-tasks will be practised separately before the whole task is tackled. In progressive part-training each part-task will first be practised separately and subsequently together with the preceding part-tasks. Finally, in cumulative part-training, only the first part-task will be practised separately, subsequently a second part-task is added, etc.

Benefits of part-task training

Part-training can be applied for two different reasons. The first reason is that part-training can often be carried out with relatively simple training media. If training with these ‘part-task trainers’ replaces training with more sophisticated media (e.g. full mission simulators), training costs can be reduced. The second reason is that part-task training can be more efficient, i.e. it speeds up the learning process and thus saves training time. It is generally assumed that the increased efficiency of part-training will occur only in the initial phase of the learning process and will be particularly beneficial if the task is highly complex and if trainees are of lower than average ability. In a case where the task is too complex for the trainee, exposure solely to the whole task may even prevent the learning process from starting.
However, reviews of training research (Wightman & Lintern, 1985, Teague, Gittleman & Park, 1994) indicate that in the majority of cases part-training is less efficient than whole task training. Whole-task training thus is the preferred method if the task is sufficiently simple and can be reasonably approximated by the trainee. Only when the whole task is dangerous or highly complex and can be easily divided into part-tasks is part-training the better choice. Teague and colleagues (1994) argued that with regard to recall and recognition context-dependent methods are favoured over context-independent methods. However, if the acquired knowledge and skills have to be selectively applied in a variety of situations, context-independent presentation methods are recommended.

2 A model for part-task efficiency with one part-task

In this study ‘speed-tasks’ (or ‘speed-based tasks’) are investigated. These are tasks that allow the skill-level to be measured principally by the trainees’ speed of performance, once completion of the task can be taken for granted. Crossman (1959), in his classical study of skill acquisition in cigar production, used the term speed-task. The production of one cigar, with specified quality, could be measured merely in terms of production time (‘trial time’) or its reciprocal: production rate, i.e. number of completed products per unit time.
Throughout this study, the term ‘trial time’ rather than ‘response time’ is used, to indicate the time needed to successfully complete a trial on a speed-task. After all, a complex task encountered in the real world usually requires a series of responses rather than a single response and hence ‘response time’ is an inappropriate term.
Learning models for speed-tasks have sometimes been expressed as *rate* models (e.g. Restle & Greeno, 1970, Mazur & Hastie, 1978, Gallistel & Gibbon, 2000). These models assume that learning is based on the temporal intervals between events and the reciprocals of these intervals, the rates at which events occur. In this study we define rate ς as the reciprocal of the time interval between subsequent successful trial completions, i.e. as the reciprocal of trial time. Series of such trial times $\{T_1, .., T_n\}$ are measured to investigate the changes that occur in individual skill level during practising a task. Hence, the rate ς at which a trainee completes the n^{th} trial on a task is by definition:

$$\varsigma = \frac{1}{T_n}. \qquad (1)$$

It is assumed that this rate ς increases linearly with training time (i.e., cumulative trial time: $t = T_1 + T_2 + .. + T_n$). Following this assumption, a functional expression for the expected rate $E[\varsigma(t)]$ at which subsequent trials on a whole task will be completed is:

$$E\left(\varsigma(t)\right) = a\,t. \qquad (2)$$

According to equation (2) the expected rate increases in proportion to training time t. The parameter a is a proportionality constant. It represents the increase in rate ς per unit training time t. Since the dimension of t is s, and ς has the dimension trials/s, parameter a must have the dimension trials/s^2. If we were to plot the *learning curve* $\varsigma(t)$ against t, the parameter a would represent the tangent (slope) of the best fitting straight line through this curve.

Now, assume that before practising the whole task, the trainee has practised with a part-task during a period of practice time t_*. If there is transfer between the part-task and the whole task, part-practice would cause the slope a of the learning curve to change with a quantity a_* and would cause a constant bias ς_* in whole-task performance. In accordance with equation (2), a functional expression for the rate at which trials are completed during subsequent whole-task practice then becomes:

$$E\left(\varsigma(t)\right) = \varsigma_* + (a + a_*)\cdot(t - t_*). \tag{3}$$

It is further assumed that the change in slope a_* is a linear function of part-task practice time t_*[1]. This gives the 'transfer function':

$$a_* = b\cdot t_*, \tag{4}$$

in which the parameter b is a proportionality constant, representing the constant increase in learning speed on the whole-task per unit practice time t_* with the part-task. Parameter b has dimension trials/s^3 (since a_* has dimension trials/s^2 and t_* has dimension s).
When we substitute equation (4) into equation (3), we obtain:

$$E\left(\varsigma(t)\right) = \varsigma_* + a\cdot t + b\cdot t\cdot t_* - b\cdot t_*^2 - a\cdot t_*. \tag{5}$$

Optimal transfer of part-training occurs when practice with the part-task produces the maximum skill-level on the whole-task at the end of the training. Thus, when total training time has a limited duration in which both the part-task and the whole task must be practised, the 'logistics' question is: How can one achieve the highest rate ς on the whole task at the end of the training? In other words, we must find the value for part-task practice time t_* that maximises the expected rate $E[\varsigma(t)]$ given a fixed (limited) training time t.
A functional expression for the value of t_* that maximises $E[\varsigma(t)]$ can be found by taking the first derivative of $E[\varsigma(t)]$ in equation (5) with respect to t_* and setting this derivative to zero[2], which gives:

$$b\cdot t - 2\cdot b\cdot t_* - a = 0. \tag{6}$$

Hence, the optimal practice time t_* with the part-task is:

[1] For ease of exposition we silently assume that ς_* is an arbitrary constant, independent of t_*.

[2] To find a maximum it is also necessary for the second derivative of $E[\varsigma(t)]$ to be negative, which, in this case, requires that parameter $b>0$.

$$t_{*opt} = \frac{1}{2}\left(t - \frac{a}{b}\right). \qquad (7)$$

Note that with any combination of positive values for the constants *a* and *b,* the optimal training time t_{*opt} with the part-task is less than fifty per cent of the total training time *t*. The solution of equation (7) can be substituted into equation (5) to give the corresponding optimal performance:

$$E\left(\varsigma \,|\, t\right)_{opt} = \varsigma_* + \tfrac{1}{4}\tfrac{a^2}{b} + \tfrac{1}{2}\left(a\right)t + \tfrac{1}{4}b\,t^2. \qquad (8)$$

The optimal training time t_{*opt} with the part-task and the corresponding optimal performance can be calculated once values for the free parameters *a*, *b* and ς_* are known (or rather, when these parameters can be estimated from data collected during training).

More elaborate models for transfer can be obtained when formulations like those of equation (5) are based on more general models for the learning curve, rather than on a simple linear function (2). Moreover, the model could be based on more general transfer functions than the simple linear function of equation (4), and the model could be further generalised for a multiple part-task scheme, rather than a simple scheme with one part-task only. However, for current purposes, and in the absence of evidence needed for a more elaborate model, the simple model of equation (5) will be investigated empirically.

3 Method

Tasks

In the two different versions of the Space Fortress-game (SF-game) used in this research and described below, the display contains a rotating fortress in the centre and a manoeuvrable spaceship, which has a starting position in the lower right corner of the display. The trainee controls the spaceship's flight with a joystick. The trajectory of flight can be controlled by rotating the ship and applying thrust (which causes the ship to accelerate). The ship continues to fly in the direction in which it is pointing, unless it is rotated and thrust is applied. This 'control law' significantly contributes to the complexity of the task, since novice trainees do not learn the law intuitively or easily.

The part-task contains only a subset of the game elements of the full SF-game (Mane & Donchin, 1989). This part-task was used previously by Frederiksen & White (1989). The trainee controls the spaceship's flight with a joystick and fires missiles from the ship by pressing a fire button on top of the joystick. The trainee's task is to attack the fortress by hitting it ten times with a missile, at intervals of at least 250 ms, before destroying it with a burst of two shots (fired at an interval of less than 250 ms).
The fortress defends itself against the ship. It does this by rotating to face the ship and then tracking the ship's movements while firing shells at it. When the ship is hit for the fourth time by a shell from the fortress, it is returned to its starting position. When this happens, the shot counter, which counts the hits scored against the fortress, is set to zero. A trial on the task finishes as soon as the fortress is destroyed.

The whole task is the full SF-game. The fortress is protected by moving 'mines' which emerge on the display periodically. These mines chase the ship. Unless the trainee takes action, these mines will hit the ship. Moreover, when a mine is present on the display, missiles fired at the fortress have no effect. Thus, the mine has to be eliminated by a missile immediately. However, if the trainee fails to hit the mine within 10 seconds, the mine disappears from the screen automatically. The interval between the disappearance of one mine and the appearance of the next is four seconds, during which time the trainee can fire at the fortress. When the ship is hit for the fourth time by either a mine or a shell from the fortress, the ship is returned to its starting position and its shot counter is set to zero. As in the case of a part-task, a trial on the task finishes as soon as the fortress is destroyed.
What makes the whole task even more complicated is that the trainee has to distinguish between two types of mines, and react accordingly. The more difficult mine can be identified by a letter

that appears in the information panel at the bottom of the screen (prior to each five-minute block of play, the trainee is presented with a new set of three letters that are used to identify ‘difficult’ mines). The appearance of a difficult mine requires the trainee to press the right (‘identification’) button on the mouse twice of an interval of 250-400 ms before the mine can be destroyed by a missile. The ‘easy’ mine can simply be destroyed by hitting it with a missile without pressing the identification button. However, if a trainee mistakenly presses the identification button and the mine is not an ‘easy’ one, the mine becomes invulnerable to missiles; then it cannot be eliminated and will either hit the ship or automatically disappear after 10 seconds. Since missiles fired at the fortress have no effect when a mine is present, the trainee can choose whether to avoid the invulnerable mine and wait for it to disappear or let it damage the ship. Another complication in this task is that the supply of missiles is limited, and the stock has to be monitored in the information panel at the bottom of the screen. An extra supply can be obtained by using ‘resource opportunities’. The availability of these opportunities are indicated by a random sequence of symbols (&, #, $, %, !, etc.) which appear in the centre of the display (beneath the fortress). When the $ symbol appears for the second time in a row, the trainee can get extra missiles by clicking the middle button of the mouse. As with the part-task, a trial finishes as soon as the fortress is destroyed.

<u>Trainees</u>

Twelve male university undergraduates aged between 20 and 23, with normal vision, participated in the study. Trainees were recruited via an advertisement in the University magazine of Utrecht University. In total 36 trainees were selected from a larger group of 51 candidates by means of the Aiming Screening Task (AST), a task that is known to be a reasonable predictor for training success on this task (see Foss, Fabiani, Mane & Donchin, 1989). An AST-score of 740 points was the minimum score required for participation in the study. As the current study is part of a larger training study, the sixteen trainees in the current study are a balanced subset of the full set of 36 trainees who participated in the larger study. The subset has the same average AST-score (870 points) as the full set, and each trainee with an above-average AST-score is paired with a trainee with a below-average score. None of the trainees reported playing video games for more than 4 hours per week. Trainees were paid 30 Euro per day plus a bonus of 68 Euro upon completion of the experiment.

<u>Procedure</u>

Trainees were assigned either to the whole task group or to the part-task group. The assignment was balanced between the two groups on the basis of the AST-score achieved. The six trainees assigned to the whole-task group practised with only the whole task (the full Space Fortress game) and received no previous practice training on a different task. The six trainees assigned to the part-task group first practised with the part-task and thereafter practised with the whole task. Two trainees of the part-task group transferred to whole-task practice after $t_* - 6000$ s (100 minutes), two trainees transferred after $t_* - 12000$ s (200 minutes) and two trainees transferred after $t_* - 36000$ s (600 minutes ℑ 10 hours).

Total practice time (time-on-task) was 16 hours in total for all trainees in both groups. To this end, eight training days over a five-week period were scheduled for each trainee. During a training day, the trainee would complete three training sessions consisting of eight blocks of five minutes each, separated by two breaks of twenty minutes. The effective time-on-task was thus forty minutes per session and 120 minutes per day. Trainees were allowed to take one-minute breaks between five-minute blocks. The data collected with the six trainees in the whole-task group have been published previously in Roessingh, Kappers and Koenderink (2002). The data collected with the six trainees in the part-task groups have not been previously published.

Software and equipment

The experiment room contained individual computer stations in separate cubicles. Each computer station was equipped with a PC with 80386 processor and a joystick of type FlightStick (CH-products). The joysticks were modified so that they could be connected to an A/D converter card (DataTranslation) in the PCs. The fire-button on the joystick and the three other response buttons were connected to a timer card in the PC. A camera system was installed in the cubicles to control the course of the experiment.

The original SF software was made available by the Dept. of Psychology, University of Illinois at Urbana-Champaign. To facilitate Task 1 and Task 2, the software was modified to remove the specified components of the full SF-game. The software was also modified to record additional parameters, in particular total time-on-task and trial-times, with a timing accuracy of 50 milliseconds.

Further training materials

After screening and well before the start of the experiment, the trainees received the instruction booklet for the SF game by mail at their home address. This instruction booklet specified the rules of the game and explained how to control of the space ship. No reference was made to specific tactics or strategies. The trainees were instructed to study the booklet carefully before the experiment began.

4 Results

Whole-task learning curves

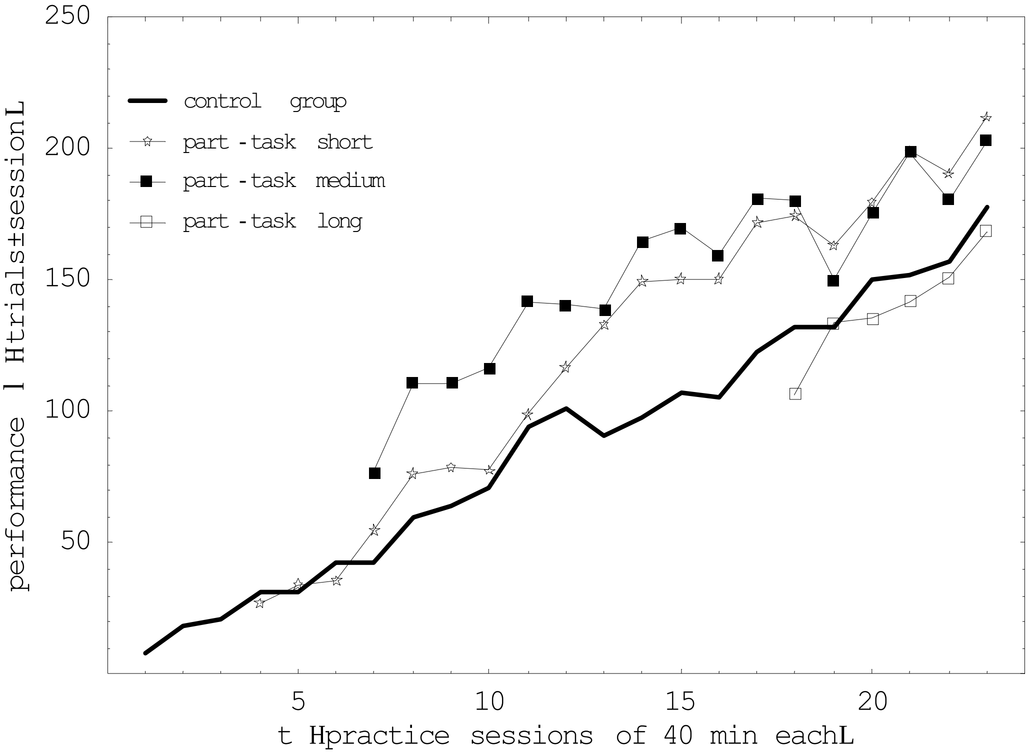


Figure 3: Average learning curves with the whole-task for the control group (6 trainees, long solid line) and for each part-task condition (2 trainees per condition, after short, medium and long training on the part-task).

Figure 3 represents learning data of all trainees during practice on the whole task, the full SF-game. The horizontal time axis denotes practice time in units of 40 minutes each (each of the 24 practice-sessions took 40 minutes). The vertical axis denotes task performance (the number of fortresses destroyed). Hence, each data point is the number of fortresses destroyed in a particular session.

The thick solid line is the learning curve for the whole-task (control) group. Performance per session has been averaged over the six trainees in this group. The line with the star-symbols is the average learning curve of the two trainees who transferred to the whole task after ℑ100 minutes of part practice. The somewhat shorter line with the filled box-symbols is the average learning curve of the two trainees who transferred after ℑ200 minutes of part practice, and the shortest line is the average learning curve of the two trainees that transferred after ℑ600 minutes of part practice.

The relative location of the learning curves of figure 3 suggests that practice with the part-task generally had a positive effect on whole-task performance, particularly for the trainees who transferred after 100 and 200 minutes. Moreover, the curves for these trainees suggest that the latter made more efficient use of training time.

<u>The "linear rate assumption"</u>

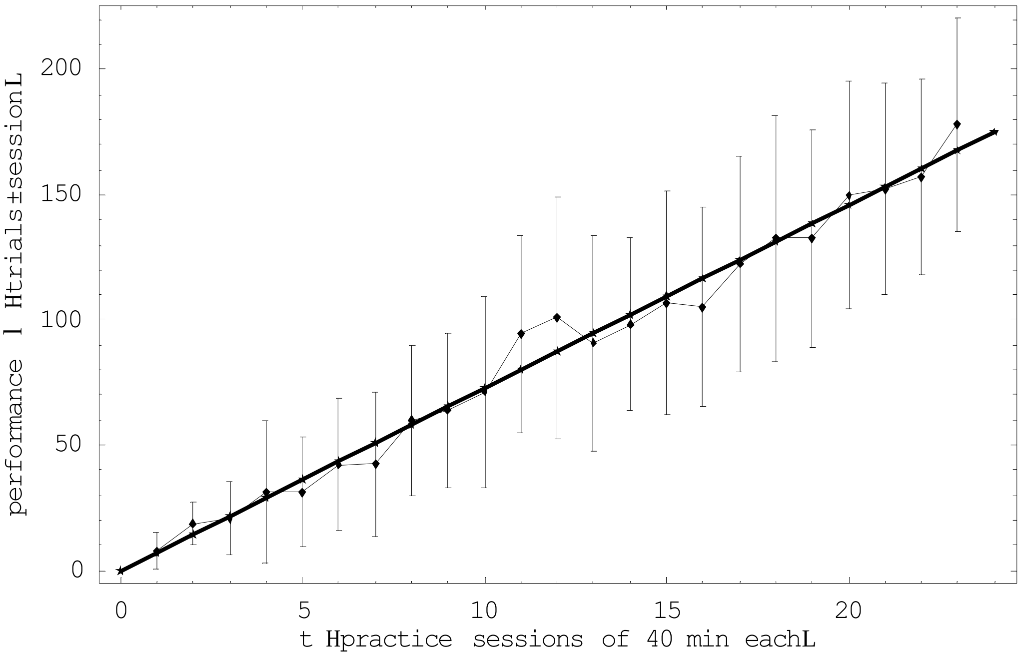


Figure 4: Learning curve for the control group with the best fitting model $\varsigma=a\,t$ (the straight solid line). Error bars indicate the standard deviation in performance over the six trainees.

The model presented for part-task transfer is based on the assumption that the rate at which trials on a speed-based task are completed will increase linearly with practice time; this was expressed by the formula $E[\varsigma(t)]=a\,t$, i.e. equation (2).

To check whether this assumption is correct, the learning curve of the control group is represented separately in figure 4. As with figure 3, performance ς is plotted against time t. The error bars represent the standard deviation in the performance score ς of the six trainees. The percentage of variance accounted for by the linear model of equation (2) is 90 per cent (R^2=0.90). The slope a of this model can be estimated from the data, which slope is 7.3 trials/session $\cdot$session (1.3 $\times 10^{-6}$ trials/s^2). The null-hypothesis for the straight-line fit, which states that the slope a equals zero, has to be rejected ($T(143)=34.7$, $p \leq 10^{-6}$).

The "linear transfer assumption"

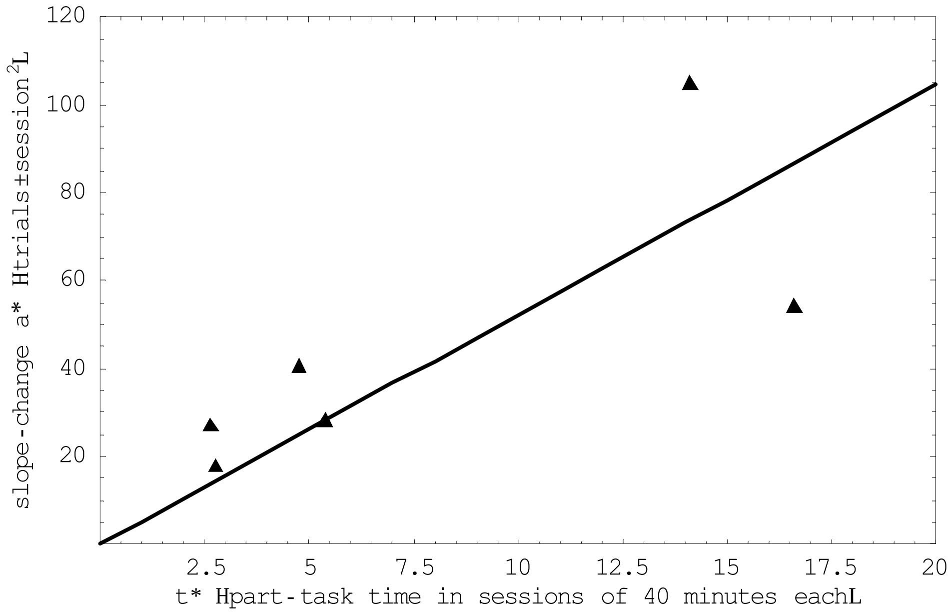


Figure 5: Change in slope (a_*) of the whole-task learning curve as a function of practice time t_* with the part-task. Each data point corresponds to the calculated slope change a_* of a trainee transferring to the whole task after t_* minutes. The fit of the model $a_*=b \cdot t_*$ is based on six data points (six trainees).

The other basic assumption of the model for part-task transfer concerns the linearity of transfer from the part-task, the assumption being that the increase in the tangent (slope) of the whole-task learning curve is proportional to practice-time with the part-task.

In the preceding section, the assumption that the learning curve during whole-task practice is a linear function was considered. This provided the basic learning curve equation $\varsigma=a \cdot t$. It was assumed additionally that part-task practice with duration t_* causes the slope a to change with a fraction a_*. More specifically, it was assumed that the slope-change a_* is linear with practice time t_* on the part-task, such that the slope-change a_* satisfies the equation $a_*=b \cdot t_*$, cf. equation (4).

In figure 5, the slope-change a_* is plotted for the six trainees who practised with the part-task. This slope-change a_* for each of the six trainees has been calculated as the difference between the slope a of each of these trainees and the average slope a of the trainees in the control group (figure 4). The horizontal axis plots the number of minutes t_* that the trainees spent practising the part-task. The solid line in figure 5 is the best fitting model $a_*=b \cdot t_*$ with ordinary least squares. The constant model parameter b is estimated to be at 5.2 trials/session^3 (~$3.6 \cdot 10^{-10}$ trials/sec^3). The linear model accounts for 86 per cent of the variance in these six data points (R^2

= 0.86) and b is significantly different from zero ($T(5)=5.5$, $p<0.003$). Although the fit is based on six data points only, the linear transfer assumption does not seem unreasonable.

Optimal training time for the part-task

Once an estimate of the constants a and b is obtained, we can use equation (7) to determine the optimal training time t_{*opt} with the part-task. In the preceding sections we estimated the slope a of the whole-task learning curve to be 7.3 trials/session^2 and we estimated the constant b to be 5.2 trials/session^3.
Since total training time t in this experiment was fixed at 24 sessions (of 40 minutes each), we can calculate t_{*opt} with equation (7) as:

$$t_{*opt} = \frac{1}{2}\left(24 - \frac{7.3}{5.2}\right) = 11.3\, sessions .$$

Expressed as a percentage of total training time t, optimal training time with the part-task is:

$$\frac{t_{*opt}}{t} = \frac{11.3}{24} \approx 47\% .$$

5 Discussion

In this study, two groups of trainees received experimental training with a complex task: the Space Fortress game (SF). We used SF because this game is a representative skill trainer for complex tasks encountered in the real world, such as flying an aircraft. The statement that SF is representative for this type of task is supported by field studies at flight schools where SF has been used in flight training. Examples are research with the Israeli Air Force by Gopher, Weil & Bareket (1992, 1994), with the US Army by Hart & Battiste (1992) and with the US Air Force by Vidulich, McCoy & Crabtree (1995).

In the experiment described in this research, the control group received training with the full SF game only. The experimental group first received part-task training with a simpler version of the game, from which the cognitive components were removed such that the emphasis was on manual control. We analysed the learning curves of the trainees in both groups in order to verify a quantitative model for skill transfer. Skill transfer (transfer of training) deals with the degree to which learning a target task (in this case, the full SF-game) is facilitated by the prior learning of another task (in this case the part-task, the simpler version of the SF-game).

<u>Testing the two assumptions of the model</u>

The model presented in this paper is based on two simplifying assumptions. The first is the “linear rate assumption”, which states that individual skill-level on a speed-based task (measured as a performance rate) increases linearly with practice time. The second is the “linear transfer assumption”, which states that there is a linear relationship between the amount of prior practice with the part-task (measured in units of practice time) and the slope of the individual learning curve measured on the target task.

The first assumption, the linear rate assumption, sounds odd, since people tend to think that learning is initially fast and then gradually slows down towards an asymptote; hence learning curves are usually considered to be non-linear. Nevertheless, the present data show that for complex speed-tasks, i.e. tasks with no speed-accuracy trade-off and ample opportunity for speed-improvement, the linear rate model is an approximate description of the data. It should be noted that alternative, more complex, models, such as higher-order linear models or non-linear models have not been tested. In future research, plausible alternatives for the linear rate model could be developed and tested against it. At the present time, the linear rate model seems a reasonable approximation for 16 hours training with the full SF-game, presumably since this task is sufficiently complex and interesting to guarantee a much longer skill acquisition process until the asymptote is reached. It is not within the scope of this paper to present a theoretical justification for the linear rate assumption. However, such theory can be found in Roessingh et al (2002).

The rationale of the second assumption, the linear transfer assumption, and its plausibility, are similar to the rationality and plausibility of the first assumption. The interpretation of a time-linear increase in performance rate as a result of repeatedly practising a task, is that during practice there is linear transfer from one time-unit to the next. Thus, given the plausibility of time-linear transfer within a single task, a similar transfer characteristic between different tasks should be equally plausible; this provides us with the basis for the linear transfer assumption. Since this assumption could only be analysed and verified on the basis of the learning curves of six trainees in the experimental group, more research is needed to further test and understand skill transfer in the acquisition of complex skills.

<u>Predictions of the linear transfer model</u>

We argued that, on the basis of the model presented, the optimal training schedule can be predicted, given the veridicality of its assumptions and appropriate estimates for the parameters *a* and *b*. In the results section we provided the optimal schedule for the training that we used in the experiment. But even in the absence of such appropriate estimates, the model makes interesting predictions. For example, it should be noted that, for any positive *a* and *b*, equation (7) implies the following inequality:

$$\frac{t_{*opt}}{t} < 50\%, \qquad (9)$$

such that optimal training time $t_{*\mathrm{opt}}$ with one part-task is always less than fifty per cent of the total training time *t*.

Note that a negative value for the slope *a* would indicate a decreasing learning curve as a result of practice, whereas a negative value for the constant *b* would be a matter of negative transfer from the part-task. In these (dubious) cases, the model presented for “optimal” transfer, based on determining optimal performance by solving from equation (5):

$$\frac{dE\left(\varsigma / t_0\right)}{dt_*} = 0, \qquad (10)$$

would identify training schedules for minimal performance rather than maximal performance. Hence, situations in which either *a* or *b* is negative should therefore be avoided. The case in which both learning curve slope *a* and transfer *b* are negative seems to be entirely theoretical.

Applications

Since the linear transfer model can be used to predict optimal training schedules, it can be applied for the professional training of complex skills. The present model is applicable to the acquisition of speed-skills in training situations with one part-task. An example is the training that pilots receive on the ground, with a part-task trainer, a procedure trainer or a simulator, to learn a set of instrument procedures. After the training on the ground, training in the real aircraft is provided. The model can be used to decide on the ideal ratio between time spent training on the ground and the time spent training in the air.

Examples of speed-skills suitable for part-training can be found in a wide range of domains: air traffic control, military aviation and industrial manufacturing, to name but a few.

It seems fairly straightforward to generalise the model to schemes with multiple part-tasks, rather than restrict it to a simple scheme with one part-task only. Moreover, the model could also be generalised to accuracy-based tasks, rather than speed-tasks only. With these generalisations the model can potentially be applied in many situations in which complex skills must be acquired and an appropriate training time schedule has to be worked out. Obviously, a practical and useful version of the model would also take into account the relative cost per unit time of part-task training and whole-task training.

6 Conclusion

The results demonstrate that a simple two-parameter model (the 'linear transfer model', which is based on two assumptions about the nature of learning and transfer) can be used to predict the optimal training time schedule in part-task training. An interesting prediction of the model is that, in training with only one part-task, more than fifty per cent of the total training time should be devoted to practice with the whole task in order to maximise performance. This prediction does not depend on the precise parameter values in the model. However, when reliable parameter values can be obtained, more accurate predictions can be made, as was demonstrated with the data from the training experiment. The linear transfer model can be applied in training situations where trainees need to acquire speed-skills, for example in military aviation.

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