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Can Human Movement Analysis Contribute to Usability Understanding?

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Abstract

Nowadays human machine interfaces are evaluated using different methodologies. These methodologies rarely consider the human movements involved in the interaction, and if so, the movements are considered in a simplistic manner. Another often neglected aspect is the relationship between the learning process and the use of the interface. Traditional approaches of cognitive modelling consider learning as just one continuous process. However there is some current evidence of concurrent processes on different time scales. This paper aims to answer, with experimental measurements, if learning actually implies a set of concurrent processes, if those processes are related to the coordinative aspects of hand movement, and how this can vary between young adult and elderly users. Two different interfaces, a washing machine and a domotic system, were analysed with 23 and 20 people, respectively, classified as men or women and elderly (over 55) or adult (between 40 and 50). The results of the study provide support for the existence of different concurrent processes in learning, previously demonstrated for motor tasks. Moreover, the learning process is actually associated with changes in movement patterns. Finally, the results show that the progression of the learning process depends on age, although elderly people are equally capable of learning to use technological systems as young adults.

Keywords: usability, Fitts law, ageing

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1. Introduction

The purpose of this work is to show how human movement analysis can contribute to an understanding of the interaction between technological devices and users. Research into Human Machine Interaction (HMI), began when machines started to become increasingly complex. The appearance of computers, with their flexibility of use and their associated complexity, was such an important milestone that by the mid 1980s computers became the paradigm of machine complexity.

One of the first approaches to HMI came from the application of Cognitive Science findings to interface design (Card et al., 1983). Since that time, many different methodologies and models have been proposed for the analysis of HMI.

Methodologies based on the cognitive approach rely on theories of the human mind that allow the analyst to make assumptions about how the user would interact with the system. The aim here is to obtain a response which coincides with the behaviour of real users. There is a wide range of cognitive models, from the simpler ones such as GOMS (Goals Operators Methods and Selection Rules) or the Model of Human Processor (Card et al., 1983), to the more complex cognitive architectures such as ACT-R (Anderson, 1983).

Usability is another approach to HMI. It was defined in the early 1990s, and it is based on collecting data from users actively participating in the interface assessment procedures Nielsen and Mack (1994).

Usability has many definitions, depending on the context in which it is applied. For instance, ISO 9241-11:1997 defines usability mainly in relation to the efficiency, performance and satisfaction of the user, because it is oriented towards usability in the workplace. Other definitions of usability, such as that proposed by Brink et al. (2002), put more emphasis on the ease of use, the ease of learning and the pleasure derived from use.

However, although users are given theoretical importance in assessment, usability issues are often addressed by expert design recommendations, the best known of which are Nielsen (1994) web design guidelines. Such guidelines sometimes rely exclusively on the experience and criteria of designers and experts, and it is not always clear how they have been validated (Health and Human Services Dept. (U.S.), 2007).

Other approaches are based on *heuristic models* (Lo and Helander, 2004)

founded on assumptions concerning ease of use, such as *simpler products would be easier to use*, and subsequent metrics to measure that assumption. Thimbleby (2004) suggests the use of matrix algebra and Markov models for usability analysis (Thimbleby et al., 2001).

Every approach has its pros and cons, but practitioners of each one usually belong to different, often diverging fields.

Both the cognitive and usability approaches consider the time required to finish a task as one of the key parameters for the assessment of the efficiency of the interface. In fact, some methodologies (such as GOMS or the Keystroke Level Model) are basically focused on the estimation of the time required by the user to perform a task. In usability analysis with users, time is always a measurement, but there are other metrics considered too, such as the number of steps required, or the perception of ease of use from the user's point of view.

Learning is also an important aspect, although it is often neglected in usability studies. Thimbleby et al. (2001) compare the behaviour of an untrained user with a purely random system (in which any part has the same probability of being activated), and the behaviour of an expert with a finite automata. Any stage of the learning process should therefore fall between the two extremes. Using this rationale, the authors obtain a theoretical curve that should be related to the ease-of-use of the system. Although most usability practitioners include ease-of-learning in their definitions, they rarely face the problem of learning directly. It is more frequent to segment users by their skill level (Faulkner and Wick, 2005), considering in this way the aspect of ease-of-use for the whole range of learning.

Learning is at the core of many cognitive models. Under the cognitive approach it is often assumed that learning follows the Power Law of Practice (Rosenbloom and Newell, 1988), which establishes that the time required to perform a task decreases with the number times the action has been repeated. Many cognitive models (such as GOMS or the Key Stroke Level Mode) explicitly assume that the learning process of an HMI follows this law of practice. However, the Power Law of Practice has recently been questioned by researchers from the field of motor development (Newell et al., 2006). These authors argue that learning is not an activity of continuous improvement, but involves different processes at different time scales, similar to the changing paradigm of motor development in children (Thelen and Smith, 1994). Newell et al. (2006) assume at least two concurrent processes: adaptation, associated with the gain in practice during one session, and learning, the

gain that remains between sessions. These authors found that the decrease in gain between sessions (the first repetition of a new session is often worse than the last repetition of the previous session) is not due to a mechanism of forgetfulness, but that the two gain rates are due to different mechanisms.

Cognitive modelling assumes that input (information coming in through the sensory systems), output (the action produced by the musculo-skeletal system) and cognition (the information processing in the brain) are separate modules. Therefore, cognitive models more or less assume that the brain establishes the next target from the information gathered by the sensory system (i.e. the eyes) and then it causes the body to move towards that target (i.e. see the Model of Human Processor in Card et al. 1983). It assumes that this movement will approximately follow Fitts' Law and that learning is produced at "brain level" and does not affect movements. However, many authors now agree that brain and body are intrinsically interconnected in such a way that cognitive processes cannot be separated from the body. Therefore, a relationship could be expected between the coordination components of movements and the learning stage, even for activities that require low motor skills, such as a simple interface use.

When dealing with HMI and elderly people, approaches differ widely. Cognitive modelling is seldom used in this case. One of the few attempts that has been made, involved a modification of the Keystroke Level Model (Charnes and Bosman, 1990). The kind of guidelines followed by usability practitioners are usually of the type: "Keep the design as simple as possible so that even elderly people can use it" (e.g. Dickinson et al. 2005). Many of these approaches reduce the possibilities of the applications for the sake of ease of use, and also limit the expertise that the user can reach. In other cases, it is assumed that elderly people refuse the use of technology. However, it is thought that this effect will tend to disappear in the future as technology becomes diffused into daily living activities (Ahn, 2004).

This paper consists of an HMI usability study of everyday products, in which the learning process of elderly people is specifically considered. The study aims to answer the following questions:

- Does learning imply a single process or do concurrent processes exist?
- Are coordinative aspects of movement related to learning how to use an interface?
- Can elderly people learn to operate complex technological interfaces or

	Adult	Elder	Total		Adult	Elder	Total
Men	4	7	11	Men	3	7	10
Women	4	8	12	Women	3	7	10
Total	8	15	23	Total	6	14	20

(a) Washing machine (b) Domotic interface

Table 1: Participants in the studies

they require simple ones?

2. Material and methods

Two different interfaces were analysed: a low-tech interface (washing machine) and a high-tech one (the tactile screen of a domotic system). Each interface was analysed in a different experimental context. Different instrumentation techniques were used to assess their adequacy.

Elderly and adult users took part in both experiments. The elderly group comprised active people over 55 years of age; the adult group was formed by people between the ages of 40 and 50.

For the washing machine experiment 23 users took part in the study (Table 1a). Each user had to perform a task (AppendixA) three times on four different days, with the days scheduled as consecutive as possible (with a difference of 1 to 5 days). 2D photogrammetry was used to analyse the movements involved in approach and withdrawal, to and from the program wheel selector. The users were instrumented with a reflective maker on the dorsal part of the hand (figure 1a). The variable of analysis was the distance from the hand to the program wheel control, within a range of 300 pixels in the image, corresponding to an approximate movement of 20 cm.

For the analysis of the domotic interface, 20 users took part in the study (Table 1b). Each user had to perform three different tasks (AppendixB) with the system in three consecutive repetitions and on four different days. As was the case, in washing machine experiment, the days were scheduled as closely as possible minimum span 1 day, maximum 5 days). The users were instrumented with an inertial sensor (I-Sens from TechNAid) (Figure 1b). Three dimensional angular velocities were recorded, but the variable analysed was the magnitude of angular velocity around the instants in which the users pushed any button on the touch screen.

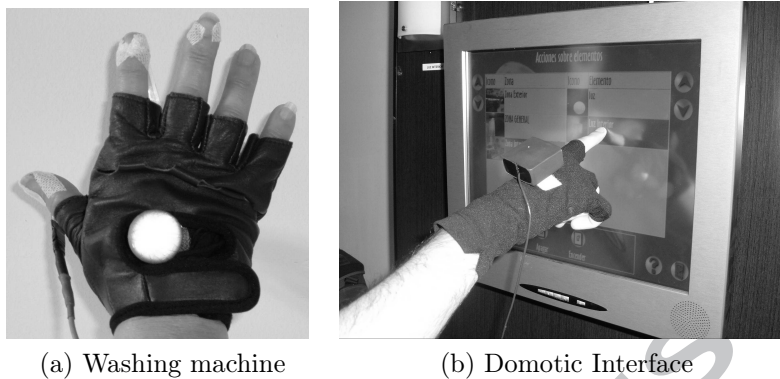


Figure 1: Instrumentation employed in the experiments

In both experiments the variables analysed were: overall time required to achieve the task and the variables related to the coordination of the movement (distance and speed for the washing machine and angular speed and its derivative for the domotic system).

Overall time was measured from the moment in which the experimenter said “go” to the moment in which the user said “finish” or “retired”. The variables were subsequently analysed to determine whether the *Time* variable differed depending on the individual characteristics of the subjects (*Gender*, distinguishing between men and women, or *Age*, distinguishing between adults and the elderly), and if it changed in the course of the learning process, during the different sessions (coded in the variable *Day*) or the different repetitions within a session (*Rep*). This was done through an ANOVA with the model (1).

$$Time \sim Day + Rep + Gender + Age + Age * Day + Age * Rep \quad (1)$$

The movement analysis consisted of four steps: (1) smoothing and differentiation of the signals; (2) parameterisation of movements through principal component analysis (PCA); (3) statistical analysis of the coefficients resulting from PCA; and (4) reconstructing curves that show the influence of significant effects on the movements.

In the first step, the recorded signals were smoothed and differentiated using a local polynomial smoothing technique (Ivaro Page et al., 2006). The original variable and its derivative were then normalised to a number of

samples (253 for the washing machine and 217 for the domotic interface), thus obtaining a parametric curve, expressing the measured variable and its derivative as a function of the samples (2). This parametric curve is, in fact, a phase portrait of the movement (i.e. see Figure 3).

$$\begin{cases} x(s) = f_1(s) \\ y(s) = f_2(s) \end{cases} \quad (2)$$

In the second step, principal component analyses (PCA) were made for all the curves, considering the value of the variables in each sample as a different variable and considering the different curves as different observations. The principal components explaining more than 5% of variance were retained. It was thus possible to refer every curve to a reduced number of parameters (3): the scores of the adjustment to the PCA that we will call adjusted coefficients (AC, c_i in the equation), and the number of curves common to all the cases: the average curve (μ), and the set of curves, that we will call *principal component curves* (PCC, $\xi_i(x, y)$ in the equation), which are similar to the functional principal components described by Ramsay and Silverman (1997). Every PCC is orthonormal and the mean of the AC for each PCC is zero.

$$f(x, y) = \mu(x, y) + \sum c_i \cdot \xi_i(x, y) \quad (3)$$

In the third step, the resulting ACs were analysed through univariate ANOVA with the model (4), where *Time* is the time required to perform a task, then introduced as a covariate in order to separate its effect from other factors. The other factors coincide with those used in (1).

$$c_i \sim Day + Rep + Gender + Age + Age * Day + Age * Rep + Time \quad (4)$$

Finally, to understand the influence of each factor on the movement curves, we obtained the marginal means of the ACs which showed significant differences due to the factor under consideration. The corresponding PCC were reconstructed with those values, and new curves were reconstructed summing those PCC with the average curves. These reconstructed curves are referred as “marginal mean curves”.

	Washing machine	Domotic System
Day	< 0.001	bf<0.001
Rep	bf<0.001	bf<0.001
Gender	0.658	bf<0.001
Age	bf<0.001	bf<0.001
Age*Day	0.937	bf<0.001
Age*Rep	0.101	bf<0.001

Table 2: p-Values for *Time* in the analysis of both systems. The conditions where significant differences were found are in bold face

3. Results

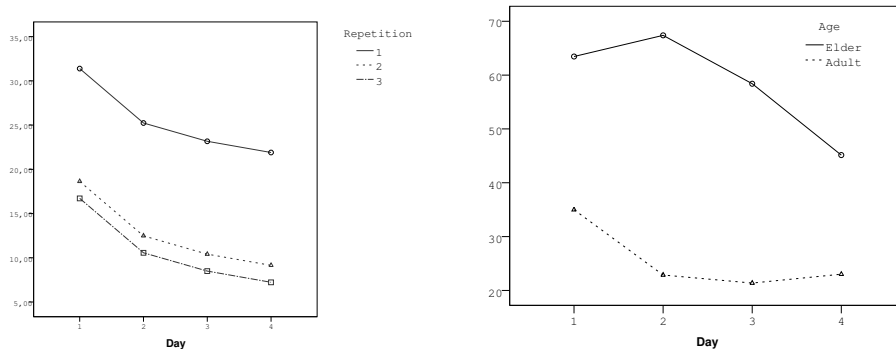
3.1. Time analysis

In the washing machine experiment, *Time* differed depending on *Day* and *Rep* (Table 2), which indicates that users achieved some improvement. The time required to perform a task decreased per *Day* and *Rep* (figure 2a); since, *Time* has an asymptotic behaviour, the time required to perform a task on the fourth day was close to a (local) minimum. There were also differences depending on *Age*: elderly people required more time than adult people (the marginal mean for elderly people is $t = 20.3s$, and for adult it is $t = 12.3s$). No differences were found per *Gender* (between men and women). No differences were either found for the interaction between *Age * Day* or *Age * Rep*.

In the experiments with the Domotic System, all factors and interactions between factors affected *Time* (Table 2). The effects of *Day* and *Rep* were similar to those of the washing machine experiment. But in this case differences were also found for *Gender* (women required less time than men to perform the task), and for the interactions. The time required by an elderly person to perform the task still decreased after the fourth session, while an adult could reach the minimum time as early as the second session (Figure 2b).

3.2. Movement analysis

Figure 3 shows the phase portrait curves of both experiments, averaged for all subjects. The phase portraits define the dynamic change of the movement variables measured in the experiments, representing their value against the value of their time derivative.



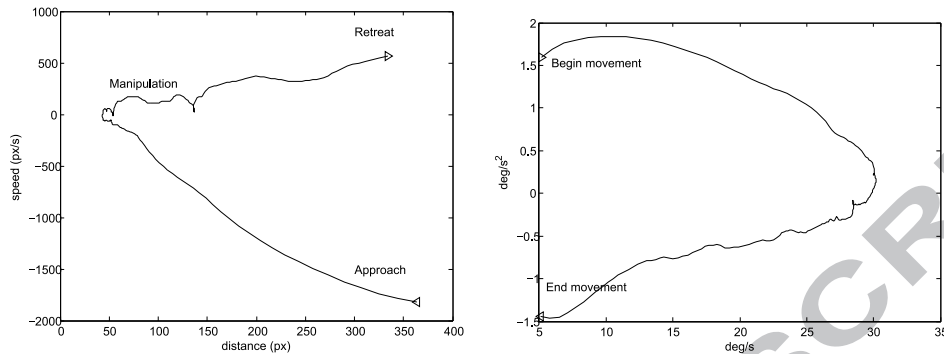
(a) Time required to perform the washing machine task per repetition and per day (in seconds)
 (b) Time required to perform the domotic interface task per age group and day (in seconds)

Figure 2: Analysis of variable *time*

In the washing machine (figure 3a) three different phases can be found:

1. The approach phase: as the hand approached the button, the distance decreased. Therefore, it is represented by the section of the curve with negative speed values. As this phase progressed, the absolute value of speed decreased smoothly. That indicates a straight movement towards the target.
2. The manipulation phase: this phase is characterized by low distance and speed values.
3. The withdrawal phase: its pattern generally mirrored the approach phase, with increasing positive values of speed as distance increased. However, the absolute value of speed was lower than during the approach, and the speed did not increase homogeneously. This may indicate a hesitating movement, that was not observed in the approach phase.

The phase portrait of the domotic system (figure 3b) is different, because in that experiment the variable recorded was not the hand position, but its angular velocity. The hand was initially addressed towards the screen in a straight direction, and it was rotated as the target point of the screen was approached. Therefore, as the movement progressed, the variable measured in this experiment (angular velocity) did not decrease, but actually increased. Two movement phases were found in this case:



(a) Distance of the hand to the button vs. hand speed in the washing machine experiment. (b) Absolute value of hand angular velocity vs. angular acceleration in the domestic system experiment

Figure 3: Average phase portrait of the movements

1. Movement start: as the angular velocity increased during this phase, it is represented by the section of the curve with positive angular acceleration, with an initially high value that decreased as this phase progressed..
2. Movement end: it is the section of the curve that mirrors the previous phase.

In this case, the hesitation (uneven ratio of angular acceleration change) was found in the second phase.

In the washing machine experiment, there were seven PCCs that explained more than 5% of variance (figure 4a), altogether accounting for 68% of the variance explained by the model. In the case of the domestic system, there were four PCC that explained more than 5% of variance, altogether accounting for 82% of variance explained by the model.

The results of the statistical analysis for the washing machine experiment (Table 3), show that AC1 explains the aspects related to the learning process, that is, the differences in the movement per day and repetition; AC2 explains the differences between user groups (elderly vs. adults and men vs. women); and there are further ACs that explain age-related and gender-related differences (AC4 and AC7, respectively).

AC1 and AC2, which were significantly influenced by *Time*, had a positive correlation with that variable. This means that those components of the movement were related to the slowness of the user doing the task. A post-

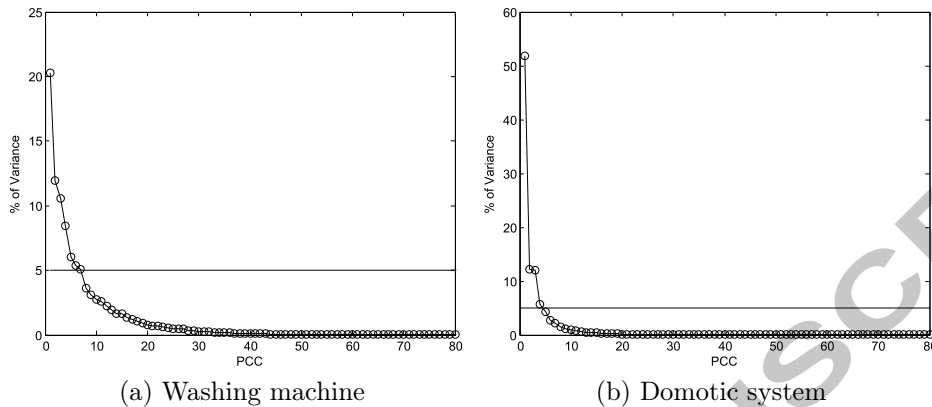


Figure 4: Variance explained by each PCC

	AC1	AC2	AC3	AC4	AC5	AC6	AC7
Day	bf0.036	0.343	0.809	0.396	0.106	0.642	0.484
Rep	bf0.003	0.549	0.455	0.933	0.360	0.121	0.079
Gender	0.293	bf<0.001	0.779	0.610	0.276	0.214	bf0.014
Age	0.107	bf0.021	0.158	bf0.014	0.935	0.425	0.553
Time	bf0.001	bf<0.001	0.686	0.318	0.688	0.512	0.239
Age*Day	bf0.031	0.275	0.954	0.213	0.504	0.549	0.595
Age*Rep	0.127	0.150	0.615	0.382	0.065	0.711	0.701

Table 3: p-Values of the univariate ANOVA per AC in the washing machine experiment. Significant differences in bold face

hoc analysis revealed that AC1 was greater on the first day and the first repetition of each day, than on the two last days and the two last repetitions of each day. The effect of the interaction between *Age* and *Day* on AC1 was that on the third day, this component of the movement was greater for elderly people, although this difference vanished on the fourth day. According to this post-hoc analysis, AC2 was generally greater for elderly and for male users, whereas AC4 was greater for elderly, and AC7 for male.

For the Domotic system, AC1 was related to most of the analysed parameters, while AC2 was related to group parameters: *Age* and *Gender*. AC3 and AC4 explained some other details of these two parameters (table 4).

As in the case of the washing machine, the components of movement that were influenced by *Time* (all but AC3), were positively correlated to

	AC1	AC2	AC3	AC4
Day	bf<0.001	0.119	0.087	0.168
Rep	bf<0.001	0.690	0.860	0.399
Gender	bf0.006	bf0.017	0.554	0.188
Age	bf<0.001	bf<0.001	bf<0.001	0.159
Time	bf<0.001	bf0.006	0.583	bf0.005
Age*Day	bf<0.001	0.447	0.481	0.728
Age*Rep	0.992	0.957	0.518	0.670

Table 4: p-Values of the univariate ANOVA per AC in the domestic system experiment. Significant differences in bold face

that variable, and the post-hoc analysis revealed similar effects of the factors over all components: those that showed differences depending on *Age* or *Gender* had greater averages for elderly and male. AC1, which also received a significant effect of *Day* and *Repetition*, was greater in the first day than in the three following days, and decreased on significantly with every repetition. The interaction between *Age* and *Day*, however, had a different effect in this case: the distance in AC1 between the adults and elderly, which was the average difference on the first day, decreased significantly on the second day, but the average ratio was restored on the third day, and the difference increased on the fourth day.

As has been established in section 2, the marginal mean curves for each factor (figures from 5 to 8) were obtained from the marginal means of the ACs which were significantly affected by the factor. For instance, to show differences in the movements of men and women in the washing machine experiment (figure 6b), the marginal means of AC2 and AC7 were obtained for both groups, and the curves were then reconstructed using (3).

Regarding the washing machine learning process (figure 5), it can be seen that the approaching speed increased gradually during the three first days, but the approach movement on the fourth day was indistinguishable from the third. The evolution of the withdrawal movement is less clear; the curve reflects an increase in the dynamic component of the movement (variations in speed were greater). Regarding the adaptation process (related to repetitions), an evolution from the first to the second repetition was found, but the second and third repetitions were almost equal. These results are similar to those obtained in the time analysis; in other words, the reduction

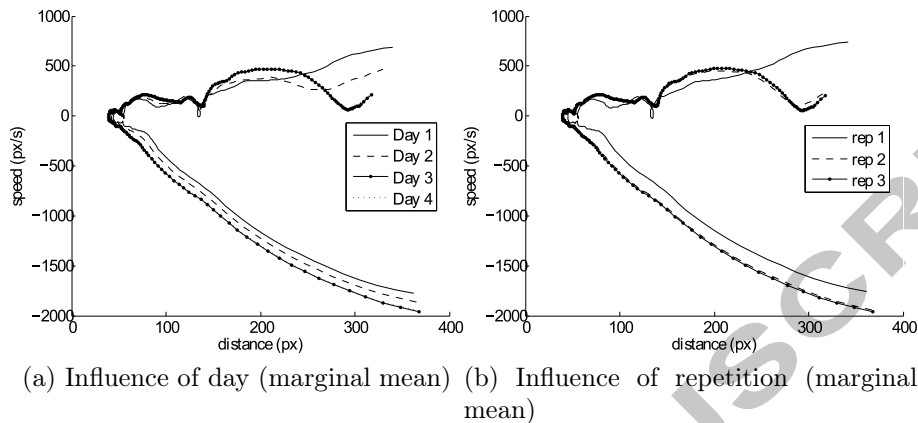


Figure 5: Average phase portraits of the movement in the washing machine experiment for the different days and repetitions, according to the ANOVA linear model. Compare with the overall average phase portrait in 3a.

in the time required to perform the task is consistent with the increase of speed. Notice that, however, the increase of speed observed during different repetitions and days was not due to the lower task completion times, since the effect of *Time* had been separated by introducing it as a covariate in (4).

Regarding *Age*, the approach movements of the elderly were slower than those of the adult, while withdrawal speeds were very similar (figure 6a). This result is again consistent with the time analysis: elderly required more time to perform a task and their movements were slower. The results of *Gender* are more surprising: women moved faster than men in both movement phases; however there were no differences in *Time*. This could imply a different movement strategy between women and men to execute the tasks: women would have employed more time “thinking” about the next action, and then performed the movement faster, while men employed less time in thinking and performed slower movements, resulting in similar times to accomplish the task for both groups: different strategies yielded the same result.

For the Domotic system, AC1 was the only parameter related to the learning process (table 4). The marginal mean curves per day and repetition (figure 7) explain how the movements changed. On the first day the movements were considerably slower than on the other three days, which show more similar curves (figure 7a). The gain in repetition is higher, and almost linear from one repetition to another. In order to analyse possible

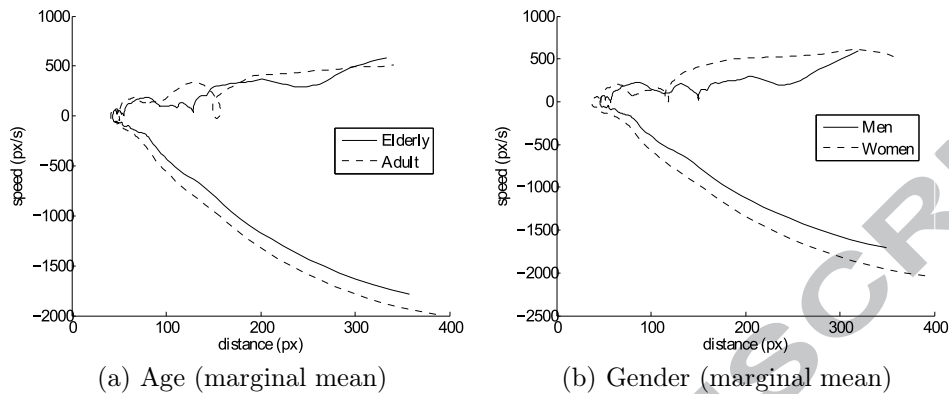


Figure 6: Average phase portraits of the movement in the washing machine experiment for the different user groups, according to the ANOVA linear model. Compare with the overall average phase portrait in 3a.

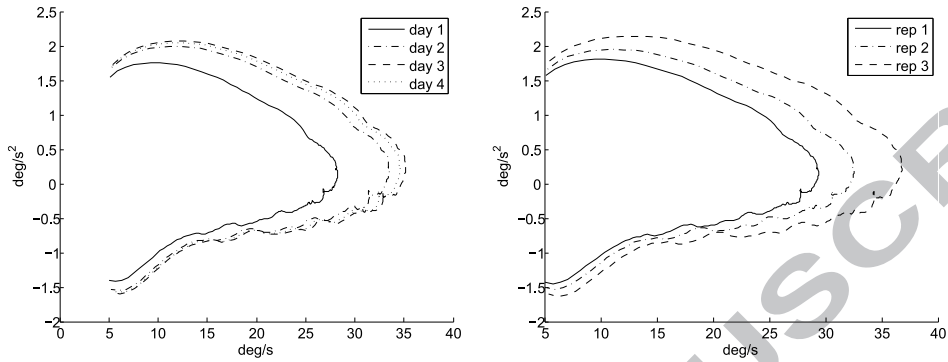
relationships between day and repetition, another univariate ANOVA was made according to model (5), but no significant differences were found for the interaction between *Day* and *Rep* (p -Value = 0.322).

$$AC1 \sim Day + Rep + Gender + Time + Day * Rep \quad (5)$$

Regarding *Age*, adult users moved faster than elderly users, and this result is consistent with the results obtained in the analysis of time, and also with the results obtained for the washing machine test (figure 8a). Women moved faster than men, which is consistent with the shorter times required to perform the tasks, as well as with the results obtained in the washing machine test.

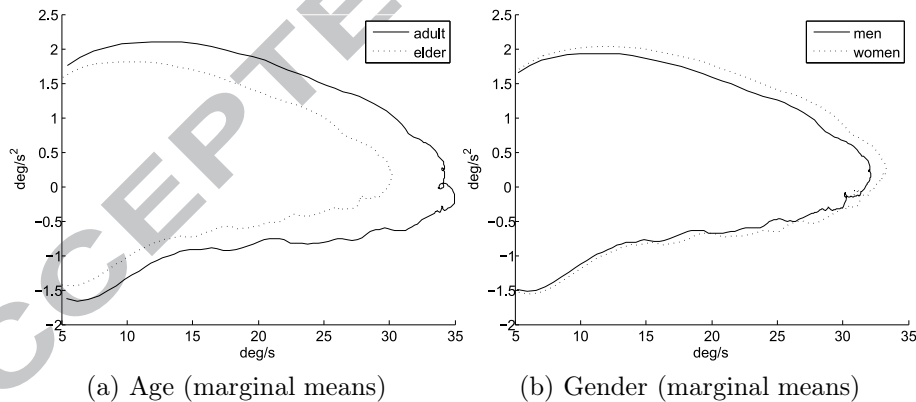
4. Discussion

First of all, it seems clear that, when using an interface, the coordination aspects of movement depend on the skills acquire while actually using it. Both for washing machines and domotic systems, movements are dependent on the number of days of user experience, and of the number of task repetitions (tables 3 and 4). Moreover, the movement pattern is related to the time that is required to accomplish a task so that faster movements are related to shorter completion times. This result, despite its obviousness, is contrast with the assumptions of some cognitive models such as the GOMS



(a) Influence of day (marginal means) (b) Influence of repetitions (marginal means)

Figure 7: Average phase portraits of the movement in the domotic system experiment for different days and repetitions, according to the ANOVA linear model. Compare with the overall average phase portrait in 3b.



(a) Age (marginal means) (b) Gender (marginal means)

Figure 8: Average phase portraits of the movement in the domotic system experiment for different user groups, according to the ANOVA linear model. Compare with the overall average phase portrait in 3b.

and the Keystroke Level Model (Card et al., 1983), as well as the ACT-R (Anderson, 1983) architecture which considers movement to be driven by the Fitts' law and, subsequently independent of the state of learning. From the results shown it seems clear that movements and cognitive processes are not independent. This could explain why some authors have found it difficult to adapt cognitive modelling to people with physical disabilities (Keates et al., 2002). Also, Fitts' Law (Fitts and Radford, 1964) does not seem to be directly applicable when a learning process is underway: the movements made towards the goal depend on the learning state of the user.

Movement analysis provides more insight into usability studies: In the case of the washing machine users, we discovered different strategies between the men and women participating in the study: although no differences were found in the time needed to accomplish the task (table 2), we did find differences in the aspects related to movements (table 3). This could imply a gender differences in the way men and women perceived the information and the way they acted to achieve the goal. This isn't considered in other research based on these aspects to the knowledge of the authors.

The results obtained support the idea of concurrent processes in acquiring skills (adaptation and learning) which goes against the idea of a unique process (learning), giving support of the theory of Newell et al. (2006). The results provide some evidence: changes in movements between repetitions within a session are different from those between sessions (figure 5). Also there were no interactions between variables when an explicit model was tested, meaning that the changes between repetitions were independent from the changes which occur between days. It can therefore be assumed that different processes are involved.

The results are also in contradiction with some generally held opinions (Dickinson et al., 2005). On the one hand, although elderly users moved slower than adults in both experiments, they were able to learn to use both systems effectively, including the domotic system (figure 2b). These results question certain approaches in the design of information and communications technologies for the elderly, that call for oversimplification of the systems.

In relation to gender issues, men were seen to be as effective as women in using the washing machine, and women were even better than men (2) in using the domotic system. No gender barriers are therefore apparent for the use of any of the products tested. However, women executed the movements faster than men in both cases, which may imply that each gender uses a different strategy.

5. Conclusions

Regarding the three questions posed in the Introduction, the conclusions reached are the following:

- Learning implies different concurrent mechanisms on different time scales, as suggested by Newell et al. (2006).
- The coordination aspects of movement depend on the learning state of the user as well as the state of the concurrent mechanisms related to learning.
- Elderly people are perfectly capable of learning to use technological devices, such as a general purpose domotic interface, although they require more time than adults for the process.

Some other results were obtained:

- Movement analysis can provide useful information related to the use of interfaces, such as the different strategies used by men and women to perform a task. Movement measures are time functions that comprise far more data than simple parameters as time consumption, or number of errors; therefore, it is possible to find subtler differences in them depending on the user characteristics, or the learning process. Moreover, the dynamic characteristics of the variables can reveal the points where users hesitate. That information may help designers to detect the weak points of a system.
- Elderly people performed slower hand movements than adults, and women moved faster than men, when interacting with the interfaces under study.
- The usual cognitive modelling strategies would have failed to model user movements during the learning phase.

AppendixA. Tasks for the tests with the user machine

Task 1

Set the program to 30^o, the spin-dry at minimum speed and include the extra rinse cycle.

Task 2

Set the program to the hottest temperature for washing, the spin-dry at maximum speed, and include the extra rinse cycle and the easy ironing mode.

Task 3

Set the system for washing in cold water and the timer to start in 2 hours.

Task 4

Set the pre-wash and the soak cycle.

AppendixB. Tasks for the tests with the domotic system*Task 1*

Start with everything turned off. The user should switch on the movement sensor for the alarm system and the external light.

Task 2

Start with the external light turned up to 100%. The user should regulate the power of the external light down to 0% and switch on the movement sensor.

Task 3

Start with the external light turned up to 100%. The user should open the blinds and turn on the internal light.

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