Chapter 3

BAYESIAN MODELLING FOR INCLUSIVE DESIGN UNDER HEALTH AND SITUATIONAL INDUCED IMPAIRMENTS: AN OVERVIEW

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Predictive pointing enables smart interfaces, which are capable of inferring the user intent, early in the pointing task, and accordingly assisting on-display target acquisitions (pointing and selection). It adopts a Bayesian framework to effectively model the user pointing behaviour and incorporate the present perturbations induced by situational impairments as well as inaccuracies in the utilised sensing technology.

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The objective of the predictive pointing system is to minimise the cognitive, visual and physical effort associated with acquiring an interface component when the user input is perturbed due to a situational impairment, for example, to aid drivers select icons on a display in a moving car via free hand pointing gestures. In this chapter, we discuss the ability of the predictive pointing solution to simplify and expedite human computer interaction when the user input is perturbed due to health induced impairments and disability, rather than a situational impairment. Examples include users with tremors, spasms, or other motor impairments. Given the flexibilities acceded by the Bayesian formulation, the applicability of the predictive pointing to inclusive design in general is addressed. Its intent prediction functionality can be adapted to the user's physical capabilities and pointing characteristics-style, thereby catering for wide ranges of health induced impairments, such as those arising from ageing. It is concluded that predictive displays can significantly facilitate and reduce the effort required to accomplish selection tasks on a display when the user input is perturbed due to health or physical impairments, especially when pointing in 3D via free hand pointing gestures.

INTRODUCTION

Interactive displays, such as touchscreens, are becoming an integrated part of the car environment due to the additional design flexibilities they offer (e.g., combined display-interaction-platform-feedback module whose interface can be adapted to the context of use through a reconfigurable Graphical User Interface GUI) and their ability to present large quantities of information associated with In-Vehicle Infotainment Systems IVIS (1-4). The latter factor is particularly important since the complexity of IVIS has been steadily increasing to accommodate the growing additional services related to the proliferation of smart technologies in modern vehicles (5). Using an in-car display typically entails undertaking a free hand pointing gesture to select an on-screen GUI icon. Whilst this input modality is intuitive, especially for novice users, it requires dedicating a considerable amount of attention (visual, cognitive and physical) that can be otherwise available for driving (4). Additionally, the user pointing gesture and input on the display can be subject to in-vehicle accelerations and vibrations due to the road and driving conditions, which can lead to erroneous selections (6). This source of perturbations is dubbed Situationally Induced Impairment and Disability (SIID). Figure 1 depicts an example of free hand pointing gestures, in 3D, subjected to high levels of perturbations (i.e., SIID) in a moving car. The notable impact of the in-vehicle SIID originated perturbations is clearly visible in the pointing motion as jolts or jumps. Adapting to the present noise and/or rectifying incorrect selections will tie up more of the user's attention. This can render interacting with the touchscreen highly distracting, with potential safety consequences (4, 7).

Predictive interactive displays, proposed in (8, 9), utilise a gesture tracker to capture, in real-time, the pointing hand/finger locations in 3D in conjunction with appropriate probabilistic destination inference algorithm. It can establish the icon the user intends to select on the display, remarkably early in the free hand pointing gesture, and in the presence of perturbations due to road and driving conditions, i.e., SIID. The smart intent-aware display then accordingly simplifies and expedites the target acquisition by applying a *pointing facilitation scheme*. This can be in the form of, among other options, expanding or colouring the intended GUI icon(s) or even selecting the predicted item on behalf of the user, who then need not touch the display surface. Therefore, predictive displays can notably improve the usability of in-car interactive displays by reducing distractions and workload associated with using them. The Bayesian formulation of the fundamental problem of intent inference, see (8), enables the predictive displays to effectively handle varying levels and types of present SIID-originated perturbations and/or user pointing behaviour as well as incorporating additional sensory or contextual data when available. It is noted that several pointing gesture trackers, which can accurately track, in real-time, a pointing gesture in 3D, have emerged lately, e.g., Microsoft Kinect, leap motion and others. They are motivated by extending Human-Computer Interaction (HCI) beyond traditional keyboard input and mouse pointing.

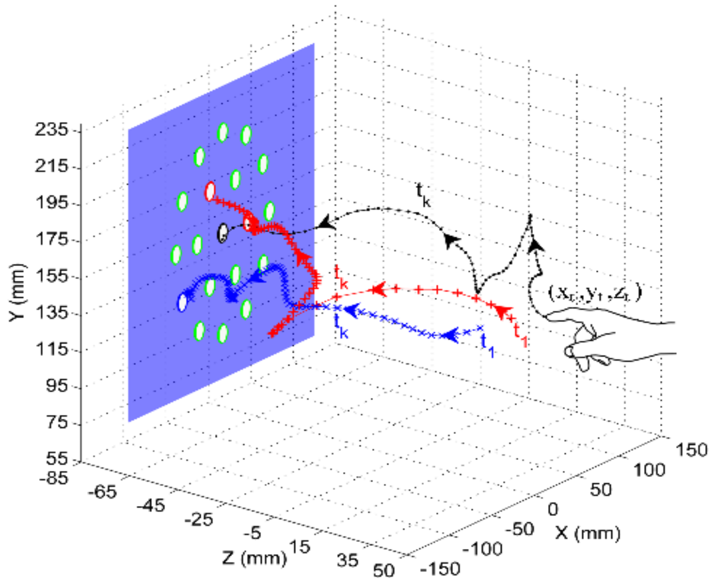


Figure 1. Full pointing finger-tip trajectories in 3D during three pointing gestures aimed at selecting a GUI item (circles) on the in-vehicle touchscreen surface (blue plane), whilst the car is driven over a harsh terrain with severe perturbations present. Arrows indicate the direction of travel over time, starting at $\mathbf{t_1} < \mathbf{t_k}$.

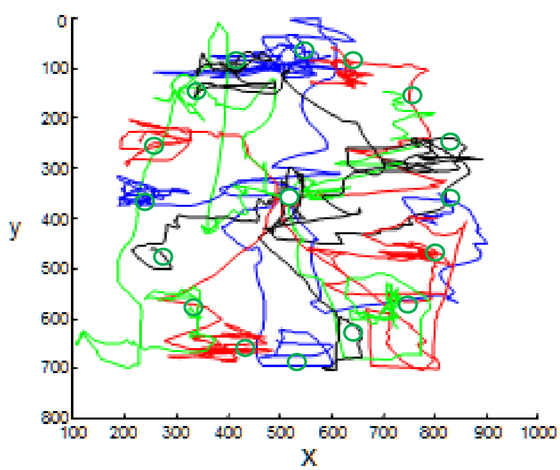


Figure 2. Several 2D mouse cursor tracks to acquire on-screen GUI icons (classical Fitt's law task, ISO 9241) for user with cerebral palsy (20). Starting position is at the centre and nominal targets (shown by circles) are distributed in a circular formation.

On the other hand, using technological devices and the ubiquitous touchscreens becoming commonplace in everyday life, whether in work or domestic environments, led to the task of acquiring targets on a graphical user interface (e.g., to select buttons, menus, etc.) being a part of modern life and a frequent human-computer interaction undertaking. Hence, facilitating on-screen target acquisition (pointing and selection), reducing the effort incurred and improving its accuracy is critical for realising effective user interfaces. This is typically tackled by applying a pointing assistive strategies (e.g., expanding icon, altering its activation area, etc.), preceded by a mechanism to establish the intended GUI icon, i.e., to identify which icon to expand or alter, for example see (10-19). Whilst the user population is diverse and includes motion impaired, elderly and non-expert users, these HCI studies often consider able-bodied computer users and focus on pointing in 2D on a computer screen using a mouse or a mechanical device. However, similar to users experiencing SIID, the pointing-selection task can be challenging for users with a motion-visual impairment, i.e., Health Induced Impairment and Disability HIID (19-24), for example, Figure 2 shows 2D mouse cursor pointing tracks of a user suffering from cerebral palsy. The prediction approaches developed for mouse pointing are also in general unsuitable for pointing in 3D using free hand pointing gestures and/or have high computational-training requirements (8). Thereby, suitable prediction algorithms for pointing in 3D under situational impairment are proposed in (8), within a flexible Bayesian framework. Statistical techniques based on Kalman filtering and advanced state-space particle filter method are employed to smooth 2D pointing mouse cursor trajectories and 3D tracks of free hand pointing gestures (8, 19, 20). They compensate for (remove) HIID and SIID related perturbations, such that the resultant 2D or 3D pointing trajectories move only in the intended direction.

In this chapter, we highlight the potential of applying the predictive display solution, which was developed for perturbations due to SIID in automotive contexts and supports pointing gestures input modality in 3D, to facilitate HCI for users with a wide range of health induced impairment and disability. This includes HIID that arises from age, and not only severe forms of physical disability. Therefore, this HCI solution can be viewed as a means to promote inclusion. Inclusive design examines designed product features with particular attention to the functional demands they make on the perceptual, thinking and physical capabilities of diverse users. A predictive display can extend the usability of the interactive displays to a diverse population of users, for example, motion impaired or able-bodied users, elderly or young users, expert or non-expert users as well as those that are situationally impaired.

Here, we exploit the transferability of HCI solutions for HIID to SIID scenarios (and vice versa) (23, 26). This transferability assumes that any human user can be impaired (disabled) in their effectiveness by characteristics of their environment, the task and the design of the GUI. Such impairment may take the form of perceptual, cognitive and physical movement functional limitations, which translate into inability. For instance, attempting to enter text on an in-car touchscreen (e.g., for navigation) whilst driving in an off-road environment presents difficulties in perceiving the interface for multiple tasks (seeing on-screen icons, outside driving environment and vehicle controls), performing the attentional tasks necessary for safe driving (track/correct vehicle movement, maintaining car controls as well as monitor/correct the texting task), and carrying out the required physical movements (pointing, pressing, steering, braking, etc.). The Bayesian intent predictor applied within a predictive display system relies on defining a Hidden Markov Model (HMM) of the pointing motion in 3D, effectively capturing the influence of the intended endpoint on the pointing finger/hand movements (8). This is distinct from previous HCI research on endpoint prediction in 2D scenarios, e.g., (11-18), which often follow from Fitt's law type analysis and uses a static setting/model. The statistical modelling approach permits capturing the variability among users, motor capabilities and the noise of the motion tracking sensor via Stochastic Differential Equations (SDE) that represent the destination-motivated pointing motion in 3D or even 2D.

INCLUSIVE DESIGN FROM DISABILITY TO HCI

Increasingly, mobile technology is proliferating, and due to the expected contribution of the Internet of Things (IoT), 5G and recent mobile communications technology, a plethora of possible applications integrating sensor networks, cloud based processing and storage and mobile contexts will present HCI challenges to interaction designers (24, 27). Challenges range from: network latencies, and lack of them; processing limitations; fusion of multiple sources of data, and the potential to overload the user's capabilities, both in terms of physical responses and also cognitive capacity. The field of inclusive design relates the capabilities of the population to the design of products by better characterising the user–product relationship. Inclusion refers to the quantitative relationship between the demand made by design features and the capability ranges of users who may be excluded from use of the product because of those features. By 2020, almost half the adult population in the UK will be over 50, with the over 80s being the most rapidly growing sector. These "inclusive" populations contain a great variation in sensory, cognitive and physical user capabilities, particularly when non-age-related impairments are taken into account. Establishing the requirement of end users is intrinsically linked to the user centred design process. In particular, a requirements specification is an important part of defining and planning the variables to be tested and measured as well as the technology use cases to be addressed during the user trials.

In particular, inclusive design is a user-centred approach that examines designed product features with particular attention to the functional demands they make on the perceptual, thinking, and physical capabilities of diverse users, particularly those with reduced capabilities and ageing. It is known, for example, that cognitive capabilities such as verbal and visuospatial IQ show a gradually decreasing performance with aging. Attending to goal-relevant, task features and inhibiting irrelevant ones is important in interaction and this is known to be affected by ageing. Attentional resources may also be reduced by ageing, such that more mistakes are made during divided attention, dual task situations (28-30).

Another perspective on inclusive design is that of ordinary and extraordinary design that aims to improve design for older, impaired users of low functionality while at the same time enhancing design for the mainstream and ordinary users in extreme environments. On this basis, design should focus on the *extraordinary* or impaired first, accommodating mainstream design in the process (31).

Not all functional disabilities result from ageing. Some common examples of non-age-related impairment include specific conditions such as stroke and head injury, which may affect any or all of perception, memory and movement. Other conditions are generally associated with movement impairment. For example, Parkinson's disease and cerebral palsy involve damage to the brain causing effects such as tremor, spasms, dynamic coordination difficulties, and language and speech production impairment. Of course, many other conditions such as Down's syndrome and multiple sclerosis may affect cognitive capability either directly, through language learning and use, or indirectly through its effects on hearing, speech production and writing. Of all the variations discussed, many differentially affect normal population ranges of capability. They may be rapidly changing and vary in intensity both within and between individuals, leading to a demanding design environment that requires close attention to conflicting user requirements and a better understanding of user capability. Again, this confirms that interaction design for future generations of products must be inclusive.

One area offering mitigation to these challenges is design of integrated multimodal display and control technologies for ease of input and task completion (20-23). Initially, in the domain of better design for elderly and impaired computer and TV users, this work is directly transferrable to the domain of the situationally impaired interface disability users as proposed by (26) and in the form of extraordinary user interfaces (32). This approach assumes that any human user can be impaired (disabled) in their effectiveness by characteristics of their environment, the task, and the design of the user interface they are presented with. Importantly, an inclusive design approach extends beyond the scope of conventional usability methods as it must accommodate extremes of capability range or situational contexts of task or stress, that are not normally accommodated by product design. For this reason, the predictive interactive display within a Bayesian framework is well suited to the human centred design of new information-rich and multimodal interfaces. It can effectively incorporate variabilities in physical-motor capabilities, interaction style, contextual information and additional sensory data (when available), within the stochastic pointing movement and measurement models as well as the modelling priors. In this chapter, we start with a specific case, whereby the proposed statistical predictive techniques aim to facilitate the GUI icons acquisition on an in-vehicle touchscreen by a driver in a moving car, i.e., the pointing gestures can be heavily perturbed due to SIID. This has proven to be very effective in reducing the workload associated with using an interactive in-car display. Thus, the developed predictive displays framework is a promising approach to achieving substantial significant usability improvements to health impaired users, i.e., HIID, in similar pointing tasks. If so, this solution can significantly enhance the HCI capabilities of individuals with severe physical impairments such as tremor, spasm and athetosis.

BAYESIAN FORMULATION AND SUITABILITY

The free hand pointing gesture movements towards an on-screen interface item in 3D are not deterministic, but are rather governed by a complex motor system. They can also be subjected to external motion, vibrations, acceleration (e.g., in a moving platform), etc. Nonetheless, stochastic models can capture the variability in the pointing finger movements, albeit being driven by premeditated intent (33). Hence, predictions of the pointing object (e.g., finger) motion are not single fixed paths, but are rather probabilistic processes, such that the object position at a future time expressed as a probability distribution in space. By adequately incorporating this uncertainty, relatively simple models of the pointing finger motion can be used successfully to track finger movements and evaluate the corresponding *observation likelihoods* (8, 33). It is noted that the objective of a predictive pointing is not to accurately model the complex human motor system. It suffices to utilise approximate pointing motion models that facilitate establishing the on-display endpoint of a free hand pointing gesture, hence intent. Therefore, calculating the transition density of a stochastic model, for example, between two successive observation times is required to condition the tracked pointing finger state $\mathbf{X}_t$, (e.g., position, velocity, etc.) on a nominal endpoint on the display $\mathcal{D}_i$ (33). Continuous-time motion models are a natural choice in such cases, where the tracked pointing object dynamics are captured by a continuous-time stochastic differential equation. This SDE can be integrated to obtain a transition density over any time interval (8, 33). Although numerous models exist, the class of Gaussian linear time invariant models for the evolution of $\mathbf{X}_t$ has proven to be effective to establishing the user intent and also lead to a low-complexity inference procedure (8, 33, 34). This class includes many models used in tracking applications, such as constant velocity and the linear destination reverting (LDR) models.

Intent inference

Predictive displays aim to estimate, in real-time, the probability of each of the selectable icons of the displayed GUI being the intended endpoint of the undertaken pointing task. At time instant t_k where the available pointing object (finger or mouse cursor) observations (e.g., positions) are $\mathbf{m}_{1:k} = \{\mathbf{m}_1, \mathbf{m}_2, \dots, \mathbf{m}_k\}$, the system calculates

$$\mathcal{P}(t_k) = \{P(\mathcal{D}_I = \mathcal{D}_i | \mathbf{m}_{1:k}), i = 1,2, \dots, N\}. \tag{1}$$

The intended destination, which is unknown *a priori*, is notated by $\mathcal{D}_I$ such that $\mathcal{D}_I \in \mathbb{D} = \{\mathcal{D}_1, \mathcal{D}_2, \dots, \mathcal{D}_N\}$ and $\mathbb{D}$ is the set of selectable GUI items. It is noted that the locations of the interface components in $\mathbb{D}$ are known, however, no assumptions are made on their distribution or layout on the display. Following Bayes' rule, we can write: $P(\mathcal{D}_I = \mathcal{D}_i | \mathbf{m}_{1:k}) \propto P(\mathcal{D}_I = \mathcal{D}_i) P(\mathbf{m}_{1:k} | \mathcal{D}_I = \mathcal{D}_i)$, for each of the selectable GUI icons. The prior $P(\mathcal{D}_I = \mathcal{D}_i)$ is independent of the current pointing task and can represent contextual information, user profile, frequency of use, etc.

Sequentially determining the probabilities in Equation 1 demands only calculating the likelihoods $P(\mathbf{m}_{1:k}|\mathcal{D}_I = \mathcal{D}_i)$ at the arrival of a new observation (i.e., up-to-date position of the pointing finger or mouse cursor).

After evaluating $\mathcal{P}(t_k)$ in Equation 1, a simple intuitive approach to establish the intended destination at t_k is to select the most probable endpoint via

$$\hat{I}(t_k) = \underset{\mathcal{D}_i \in \mathbb{D}}{\arg\max}\, P(\mathcal{D}_I = \mathcal{D}_i|\mathbf{m}_{1:k}). \tag{2}$$

Decision criterion other than Equation 2 can be applied within the Bayesian framework, see (8). For the linear destination reverting models, Kalman filters can be used (one per nominal destination) to calculate $P(\mathcal{D}_I = \mathcal{D}_i|\mathbf{m}_{1:k})$ in Equation 1 as per (8, 34). Adopting nonlinear motion or observation models can lead to advanced statistical inference methods such as sequential Monte Carlo or other related methods for online filtering.

Linear destination-reverting motion models

Since the pointing motion is intrinsically driven by the intended on-screen icon, destination-reverting models can be suitable for predictive pointing under health or situationally induced impairments. Following the integration of their respective SDEs and assuming that the intended endpoint is $\mathcal{D}_i$, LDR models can be expressed by

$$\mathbf{X}_{i,k} = \mathbf{F}_{i,k}\mathbf{X}_{i,k-1} + \boldsymbol{\kappa}_{i,k} + \mathbf{w}_k,\; i = 1,2,\dots,N, \tag{3}$$

where $\mathbf{X}_{i,k-1}$ and $\mathbf{X}_{i,k}$ are the hidden model state vectors at two consecutive time instants t_{k-1} and t_k. For example, the state $\mathbf{X}_{i,k}$ can include the true pointing-finger location in 2D or 3D and other higher order motion dynamics such as velocity, acceleration, etc. Matrix $\mathbf{F}_{i,k}$ is the state transition and $\boldsymbol{\kappa}_{i,k}$ is a time varying constant (both are with respect to $\mathcal{D}_i$), and the motion model dynamic noise is $\mathbf{w}_k$. For $\mathcal{D}_i \in \mathbb{D}$ possible endpoints on the display (i.e., selectable GUI icons), N such models can be constructed and their corresponding likelihoods are calculated with the appropriate statistical filtering algorithm where the (also) linear observation model is given by

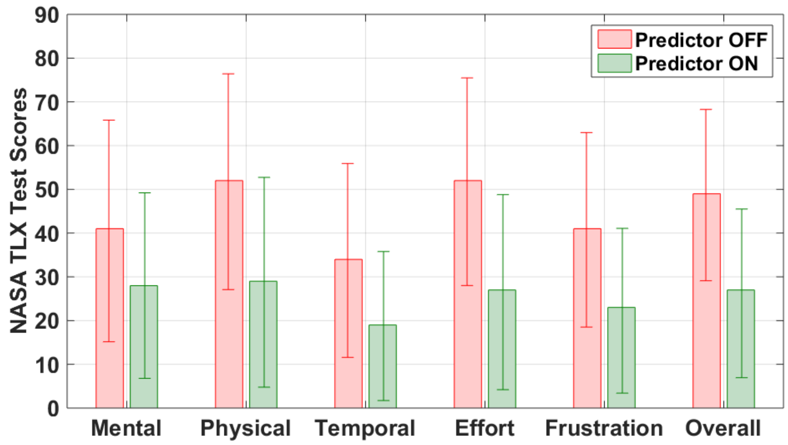
$$\mathbf{m}_k = \mathbf{H}_k \mathbf{X}_{i,k} + \mathbf{n}_k. \tag{4}$$

The noise introduced by the sensor is represented by $\mathbf{n}_k$. For more details on the LDR models and their characteristics with and without the bridging distributions, the reader is referred to (8, 33, 34).

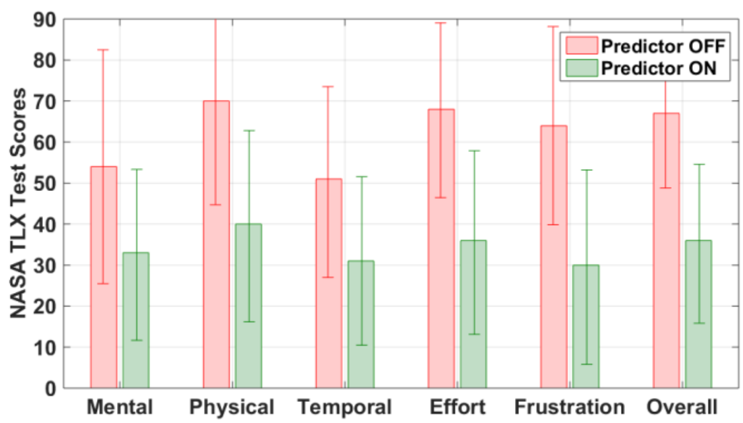
Bayesian inference with a hidden Markov model offers flexibility in terms of modelling the pointing motion with either HIID or SIID via the SDE and its integration in Equation 3. We recall that the variability in the pointing movement, e.g., due to the user behaviour and/or impairment, can be introduced through the noise element of the state $\mathbf{X}_k$ and the noise generated from the employed sensor (e.g., a particular gesture tracker) can be incorporated via the measurement noise in the observation model in Equation 4. Most importantly, the statistical filter utilised to determine the intent of the tracked object (e.g., mouse cursor in 2D or pointing finger for pointing gestures in 3D) can be applied to the same class of motion models, albeit altering the applied pointing motion model.

Smoothing noisy trajectories

The results of the N statistical filters applied to determine $\mathcal{P}(t_k)$ in Equation 1 can be employed to remove the unintentional perturbations-impairment-related movements as shown in (8, 34). However, in certain scenarios (e.g., severe perturbations) where it is desirable to maintain a simple linear motion model for the intent inference functionality, a pre-processing step/stage can be added such that the raw pointing data is filtered, e.g., using a particle filter (20, 25). The filtered track is subsequently used by the destination inference module. The effectiveness of the state-space-modelling for removing unintentional impairment-related pointing movement were demonstrated in (8, 19, 20, 25, 33, 34).



(a)



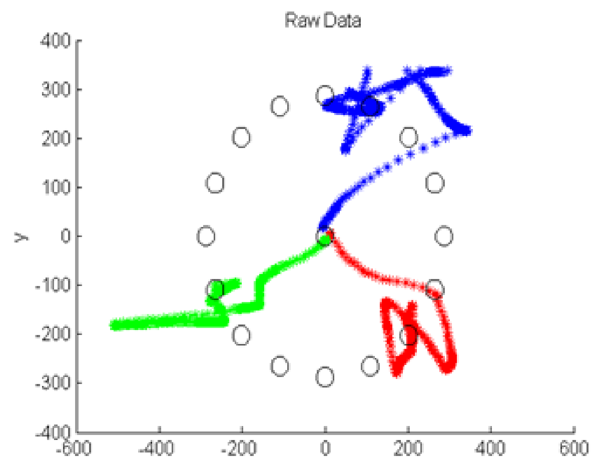
(b)

Figure 3. Workload scores for interacting with an in-vehicle touchscreen with and without the predictive capability for 20 participants under varying levels of experienced in-vehicle perturbations (9). (a) Minimum perturbations (motorway); (b) Mild-severe perturbations (badly maintained road).

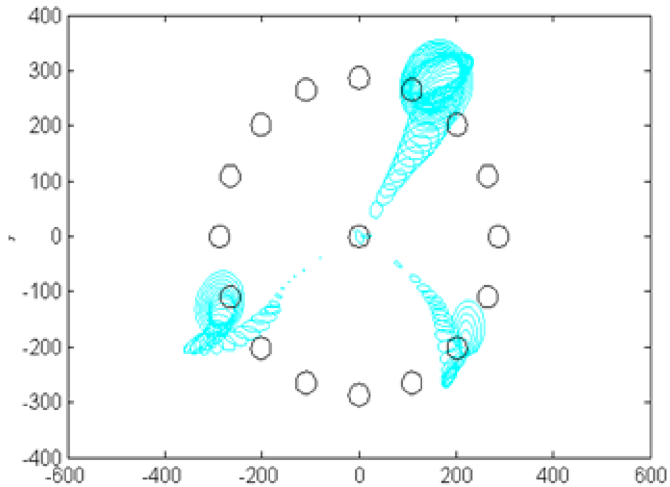
Examples: Situational and motor impairments

Figure 3 depicts results of utilising an in-vehicle predictive display under varying levels of SIID due to road/driving conditions when the predictive capability is off and on. In the former case, the experiment becomes a conventional task of interacting with an in-car touchscreen where the user has to physically touch the intended icon on the screen to select it. The benefits of the predictive display are assessed in terms of the system ability to reduce the workload of interacting with the in-car touchscreen and the pointing tasks durations T_p. NASA TLX forms, widely utilised in HCI studies, are used to evaluate the subject workload experienced by the users. In this study, a Leap Motion controller is employed to produce, in real-time, the locations of the pointing finger in 3D, i.e., $\mathbf{m}_k = [x_{t_k}\ y_{t_k}\ z_{t_k}]'$ at t_k. Pointing finger observations are then used by the probabilistic intent predictor to calculate the probabilities $\mathcal{P}(t_k)$ in Equation 1. The predictive display auto-selects the intended on-screen icon once a particular level of prediction certainty is achieved (the user need not touch the display surface to make a selection). This pointing facilitation scheme is dubbed *mid-air selection* (9). Figure 3 demonstrates that the predictive display system can reduce the subjective workload of interacting with an in-car display by nearly 50%. It can also be noticed that workload notably increases as more perturbations are experienced. Measured durations of pointing task also show that T_p can be reduced by over 35% under mild to severe accelerations-vibrations due to the road conditions (e.g., driving on a badly maintained road). Therefore, the predictive display system that uses a suitable Bayesian formulation can significantly simplify and expedite on-screen target acquisitions via free hand pointing gestures.

Figures 4 and 6 illustrate the ability of a sequential Monte Carlo method, namely the variable rate particle filter, to remove highly non-linear perturbation-related unintentional pointing movements when interacting with a touchscreen using pointing gestures in 3D and selecting icons of a GUI displayed on a computer screen via a mechanical mouse. Whereas, in figure 5 Kalman filtering is applied. The raw cursor movement data in figures 4 and 5 is for a user that suffers from cerebral palsy. Figure 4 exhibits the confidence ellipses obtained from the sequential Monte Carlo filter, which has visibly removed the health-induced-impairment jumping behaviour of the mouse cursor position and can assist identifying the user's intended destination (despite the ambiguity of the raw pointing data). On the other hand, unintentional situational-induced-impairment-related pointing finger movements in 3D are successfully removed in Figure 6.



(a)



(b)

Figure 4. Filtering noisy mouse cursor trajectories due to HIID using a particle filter and showing the confidence ellipses (20). (a) Raw noisy 2D cursor trace data; (b) filtered traces. Units on the axes are pixels.

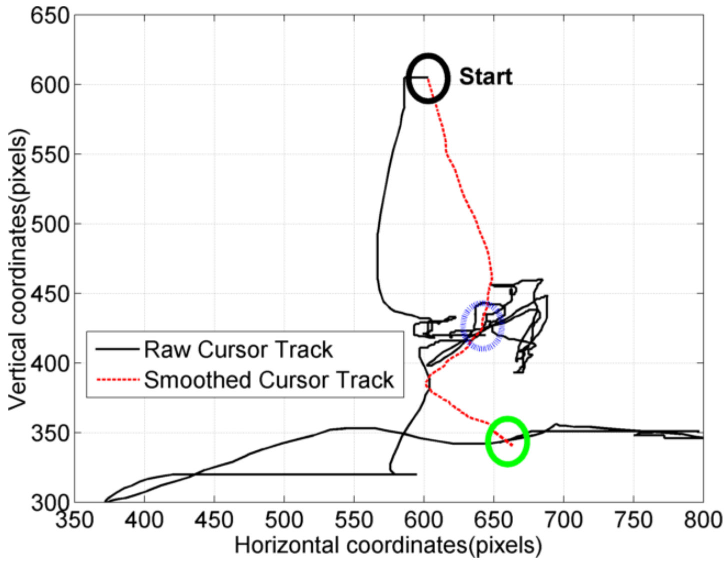


Figure 5. Smooth cursor track in 2D for a severe HIID-related perturbations (19). User is targeting two GUI icons (target 1 is the blue circle and then target 2 is the green circle). The start point is the black circle.

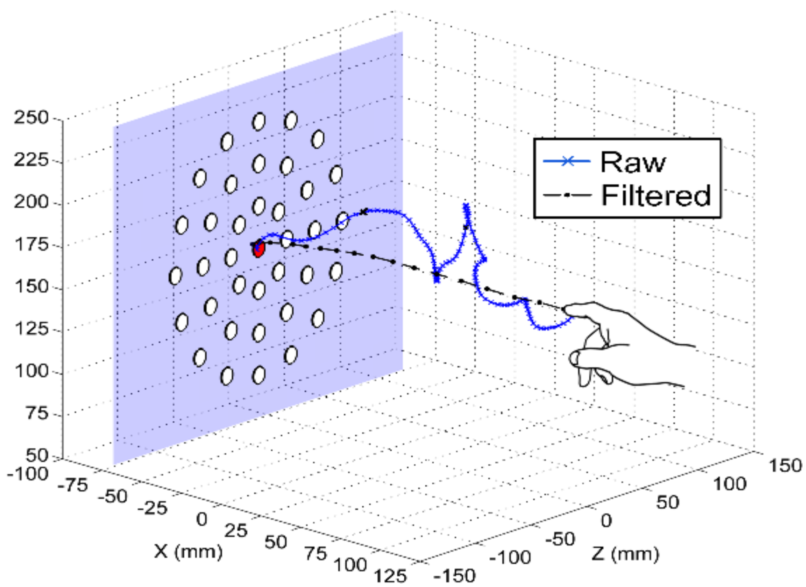


Figure 6. 3D pointing track before (blue) and after (dashed) applying a variable rate particle filter (25).

CONCLUSION

Using the Bayesian formulation developed for able-bodied touchscreen users in a perturbed environment has proved successful in improving performance and reducing workload. There is no reason to suppose these benefits may not be realised in the case of health-induced impairment and disability. We reported preliminary tests of this assumption, providing promising results. Spasm, weakness, tremor and athetosis can be mitigated or largely eliminated by the predictive approach based on the described Bayesian algorithms, original developed for automotive applications. In particular, motion impaired users, who may have difficulty pointing-selecting on interactive displays will benefit not only from prediction and automated selection (i.e. auto-selection), but also from the reduction of workload reported by the automotive trial participants, measured using NASA TLX scores.

Additionally, from an inclusive design perspective, the predictive display technology may greatly benefit those with age related or mild physical or perceptual impairments by enhancing performance in pointing-selection and reducing the associated workload. Mild functional impairments such as physical movement (reach and stretch, dexterity), visual acuity, and cognitive capacity could be improved. This predictive approach is also applicable to special purpose designs for specific cases, extreme impairment and disability. Experimental studies will be superseded by trials of the same algorithms and detection technologies with interfaces in mobile displays, walking scenarios, wheelchair use and on public transportation. Predictive displays are capable of incorporating and fusing additional sensory data or input modalities, e.g., eye-gaze or voice-based commands, via the Bayesian framework succinctly described in this chapter. In conclusion, encouraging results suggest that these specific advanced predictive algorithms for pointing and selection have utility in a range of interfaces where performance is impaired, whether by situation or by health. The health based impairment is a rich area for future investigation.

REFERENCES

[1] Burnett G, Porter JM. Ubiquitous computing within cars: designing controls for non-visual use. Int J Hum Comput Stud 2001;55:521–31.

[2] Burnett G, Lawson G, Millen L, Pickering C. Designing touchpad user-interfaces for vehicles: which tasks are most suitable? Behav Inform Technol 2011;30:403-14.

[3] Harvey C, Stanton NA. Usability evaluation for in-vehicle systems. London: CRC Press, 2014.

[4] Jaeger MG, Skov MB, Thomassen NG. You can touch, but you can't look: interacting with in-vehicle systems. Proceedings of the SIGCHI Conf. on Human Factors in Computing Systems (CHI), 2008, Florence, Italy. ACM 2008:1139–48.

[5] Bishop R. Intelligent vehicle technology and trends. Norwood, MA: Artech House, 2005.

[6] Ahmad BI, Langdon PM, Godsill SJ, Hardy R, Skrypchuk L, Donkor, R. Touchscreen usability and input performance in vehicles under different road conditions: An evaluative study. Proceedings of the 7th International Conference on Automotive UI and Interactive Vehicular Applications (AutomotiveUI), 2015, Nottingham, UK, ACM, 2015:47-54.

[7] Klauer SG, Dingus TA, Neale VL, Sudweeks JD, Ramsey DJ. The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data. National Highway Traffic Safety Administration, DOT HS 810 5942006, 2006.

[8] Ahmad BI, Murphy JK, Langdon PM, Godsill SJ, Hardy R, Skrypchuk L. Intent inference for hand pointing gesture-based interactions in vehicles. IEEE Transactions on Cybernetics 2016;46:878-89.

[9] Ahmad BI, Langdon PM, Godsill SJ, Donkor R, Wilde R, and Skrypchuk L. You do not have to touch to select: A study on predictive in-car touchscreen with mid-air selection. Proceedings of the 8th International Conference on Automotive UI and Interactive Vehicular Applications (AutomotiveUI), 2016, Ann Arbor, USA, ACM, 2016:1-8.

[10] MacKenzie IS. Fitts' law as a research and design tool in human-computer interaction. Hum Comput Interaction 1992;7:91-139.

[11] Meyer DE, Abrams RA, Kornblum S, Wright CE, Keith-Smith JE. Optimality in human motor performance: ideal control of rapid aimed movements. Psychol Rev 1988;95:340–70.

[12] Murata A. Improvement of pointing time by predicting targets in pointing with a PC mouse. Int J Hum Comput Interaction 1998;10:23–32.

[13] Asano T, Sharlin E, Kitamura Y, Takashima K, Kishino F. Predictive interaction using the Delphian desktop , 2005:133-41.

[14] McGuffin MJ, Balakrishnan R. Fitts' law and expanding targets: Experimental studies and designs for user interfaces. ACM Transactions Comput Hum Interaction 2005;12:388–22.

[15] Wobbrock JO, Fogarty J, Liu SYS, Kimuro S, Harada S. The angle mouse: target-agnostic dynamic gain adjustment based on angular deviation. Proceedings of the SIGCHI Conf. on Human Factors in Computing Systems (CHI); 2009, NY, USA, ACM 2009:1401–410.

[16] Kopper R, Bowman DA, Silva MG, McMahan RP. A human motor behavior model for distal pointing tasks. Int J Hum Comput Stud 2010;68:603-15.

[17] Ziebart B, Dey A, and Bagnell JA. Probabilistic pointing target prediction via inverse optimal control. Proceedings of the 2012 ACM International Conference on Intelligent User Interfaces (IUI); 2012; Lisbon, Portugal. ACM; 2012. p. 1–10.

[18] Pasqual PT, Wobbrock JO. Mouse pointing endpoint prediction using kinematic template matching. Proceedings of the SIGCHI Conf. on Human Factors in Computing Systems (CHI), 2014, Toronto, Canada. ACM 2014:743–52.

[19] Ahmad BI, Langdon PM, Bunch P, Godsill SJ. Probabilistic Intentionality Prediction for Target Selection Based on Partial Cursor Tracks, Proceedings of the 8th International Conference on Universal Access in Human-Computer Interaction (UAHCI). Lecture Notes in Computer Science (8515), 2014. Crete, Greece: Springer, 2014:427-38.

[20] Langdon PM, Godsill SJ, Clarkson PJ. Statistical estimation of user's interactions from motion impaired cursor use data. Proceedings of the 6th Int. Conf. on Disability, Virtual Reality and Associated Technologies (ICDVRAT), 2006, Denmark, 2006.

[21] Keates S, Hwang F, Langdon PM, Clarkson PJ, Robinson P. Cursor measures for motion-impaired computer users. In: Proceedings of the Fifth Int. ACM Conference on Assistive Technologies (ASSETS), 2002, NY, USA, ACM 2002:135–42.

[22] Gajos KZ, Wobbrock JO, Weld DS. Automatically generating user interfaces adapted to users' motor and vision capabilities. Proceedings of ACM Symposium on User Interface Software and Technology, 2007, RI, USA, ACM 2007:231-40.

[23] Biswas P, Langdon PM. Developing multimodal adaptation algorithm for mobility impaired users by evaluating their hand strength. Int J Hum Comput Interaction 2012;28:576-96.

[24] Domingo MC. An overview of the internet of things for people with disabilities. J Network Comput Applications 2012;35:584-96.

[25] Ahmad BI, Murphy JK, Langdon PM, Godsill SJ. Filtering perturbed in-vehicle pointing gesture trajectories: Improving the reliability of intent inference. Proceedings of IEEE International Workshop on Machine Learning for Signal Processing (MLSP), 2014, Reims, France, IEEE 2014:1-6.

[26] Sears A, Lin M, Jacko J, Xiao Y. When computers fade…Pervasive computing and situationally induced impairments and disabilities. Proceedings of HCI International Conference, 2003. Crete, Greece: Springer, 2003:1298-302.

[27] Atzori L, Iera A, Morabito G. The internet of things: A survey. Comput Networks 2010;54:2787-805.

[28] Petrie H. Accessibility and usability requirements for ICTs for disabled and elderly people: a functional classification approach. In: Nicolle C, Abascal J, eds. Inclusive guidelines for human computer interaction. London: Taylor Francis, 2001.

[29] Schaie KW, Willis SL. Adult development and aging. New York: Prentice-Hall, 2003.

[30] Newell AF. Older people as a focus for Inclusive Design. Gerontechnol 2006;4:190-9.

[31] Newell AF, Gregor P, Morgan M, Pullin G, Macaulay C. User-sensitive inclusive design. Universal Access Inform Soc 2011;10:235-43.

[32] Newell AF, P. Gregor. Human computer interfaces for people with disabilities. In: Helander M, Landauer TK, Prabhu P, eds. Handbook of human computer interaction. Amsterdam: Elsevier Science BV, 1997:813-24.

[33] Ahmad BI, Murphy JK, Godsill SJ, Langdon PM, Hardy R. Intelligent interactive displays in vehicles with intent prediction: A Bayesian framework. IEEE Signal Processing Magazine 2017.

[34] Ahmad BI, Murphy JK, Langdon PM, Godsill SJ. Bayesian intent prediction in object tracking using bridging distributions. IEEE Transactions on Cybernetics 2017.