

# Applying Bayesian modelling for inclusive design under health and situational induced impairments

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## ABSTRACT

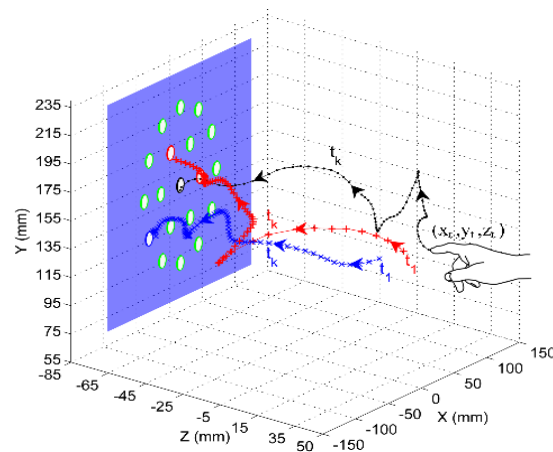
Predictive pointing enables realising smart interfaces, which are capable of inferring the user intent, early in the pointing task, and accordingly assisting the on-display target acquisition (pointing and selection). It adopts a Bayesian framework to effectively model the user pointing behaviour and incorporate the present perturbations induced by situational impairments as well as inaccuracies in the utilised sensing technology. 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 paper, we discuss the ability of the predictive pointing or display 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 or 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 an interactive display when the user input is perturbed due to health or physical impairments, especially when pointing in 3D with free hand pointing gestures.

## 1. INTRODUCTION

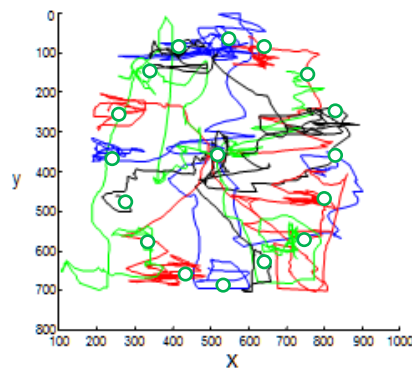
Interactive displays, such as touchscreens, are becoming an integrated part of the car environment due to the additional design flexibilities they offer (e.g. combined display-interaction-platform-feedback module whose interface can be adapted to the context of use through a reconfigurable Graphical User Interface GUI) and their ability to present large quantities of information associated with In-Vehicle Infotainment Systems IVIS (Burnett et al, 2001 and 2011, Harvey and Stanton, 2013, Jaegr et al, 2008). 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 (Bishop, 2005). 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 (Jaegr et al, 2008). 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 (Ahmad et al 2015). This source of perturbations is dubbed Situationally Induced Impairment and Disability (SIID). Figure 1 depicts an example of 3D pointing gestures 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 (Jaegr et al, 2008, Ahmad et al, 2015).

Predictive interactive displays, proposed in (Ahmad et al, 2016), 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*. The latter involves expanding the intended GUI icon or even selecting the predicted item on behalf of the user, who need not touch the display surface. 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. 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 (Ahmad et al, 2016), 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.



**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  $t_1 < t_k$ .



**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 (Langdon et al, 2006).

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 (MacKenzie, 1992, Kopper et al, 2010, Meyer et al, 1988, McGuffin and Balakrishnan, 2005, Murata, 1998, Wobbrock et al, 2009, Asano et al, 2005, Ziebart et al, 2012, Pasqual and Wobbrock 2014, Ahmad et al 2014). 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 (Ahmad et al, 2014, Langdon et al 2006, Keates et al, 2002, Gajos et al, 2007, Biswas and Langdon, 2012, Domingo, 2012), 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 (Ahmad et al, 2016). Thereby, suitable prediction algorithms for pointing in 3D under situational impairment are proposed in (Ahmad et al, 2016), within a flexible Bayesian framework. In (Ahmad et al, 2014 and 2016) 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. 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 paper, 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) as proposed in (Sears et al, 2003, Biswas and Langdon, 2012). 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 (Ahmad et al, 2016). This is distinct from previous HCI research on endpoint prediction in 2D scenarios, e.g. (Kopper et al, 2010, Meyer et al, 1988, McGuffin and Balakrishnan, 2005, Murata, 1998, Wobbrock et al, 2009, Asano et al, 2005, Ziebart et al, 2012, Pasqual and Wobbrock 2014), 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.

## 2. 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 (Atzori et al, 2010, Domingo, 2012). 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 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 (Schaie et al, 2003, Newell, 2006, Petrie, 2001). 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 (Newell et al, 2011).

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 (Langdon et al, 2006, Keates et al, 2002, Gajos et al, 2007, Biswas and Langdon, 2012). 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 (Sears et al, 2003) and in the form of extraordinary user interfaces (Newell et al, 1997). 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 paper, 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.

### 3. BAYESIAN FORMULATION AND SUITABILITY

The free hand pointing gesture movements towards an on-screen item in 3D are not deterministic, but are rather governed by a complex motor system subject to numerous physical constraints. The gesture can also be subjected to external motion, jolting, rolling, acceleration (e.g. in a moving platform). Nonetheless, stochastic models can capture the inherent uncertainty in the pointing finger movements, albeit being driven by intent. This implies that predictions of the pointing object motion are not single deterministic paths, but are rather probabilistic processes, with the pointing finger 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*. It is emphasised that the objective of a predictive pointing is not to accurately model the complex human motor (pointing) system. Formulating approximate pointing motion models that enable determining the on-display endpoint (i.e. intent) of a free hand pointing gesture suffices. 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  $\mathcal{D}_i$ . Continuous-time motion models are a natural choice in such cases, where the tracked pointing object's dynamics are represented by a continuous-time stochastic differential equation (SDE). This SDE can be integrated to obtain a transition density over any time interval. Although numerous models for object tracking exist, the class of Gaussian linear time invariant (LTI) 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. This class includes many models used in tracking applications, such as constant velocity and the linear destination reverting (LDR) models.

### 3.1 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

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

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. This prior is independent of the current pointing task and can represent contextual information, user profile, frequency of use, etc. Sequentially determining the probabilities in (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 (1), a simple intuitive approach to establish the intended destination at  $t_k$  is to select the most probable endpoint via

$$\hat{I}(t_k) = \arg \max_{\mathcal{D}_I \in \mathbb{D}} P(\mathcal{D}_I = \mathcal{D}_I | \mathbf{m}_{1:k}). \quad (2)$$

Decision criterion other than (2) can be applied with the Bayesian framework, see (Ahmad et al, 2016). 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 (1) as per (Ahmad et al 2016). 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.

### 3.2 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

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

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

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

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 (Ahmad et al, 2015 and 2016).

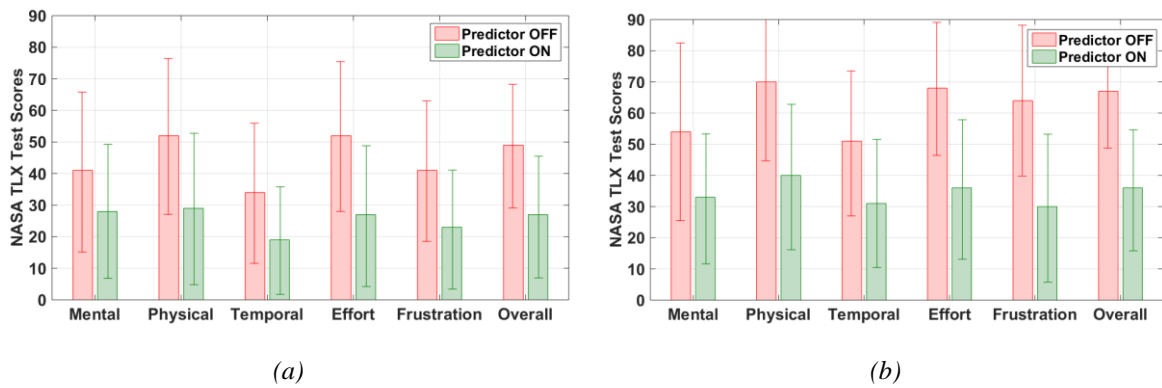
Bayesian inference with a hidden Markov model offers flexibility in terms of modelling the pointing motion with either HIID or SIID via the SDE and its integration in (3) and (4). We recall that the variability in the pointing movement, e.g. due to the user behaviour and/or impairment, can be introduced 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 equation. Most importantly, the statistical filter utilised to determine the intent of the tracked object (e.g. mouse cursor in 2D or pointing finger for free hand pointing gestures in 3D) can be applied to the same class of motion models, albeit altering the applied pointing motion model.

### 3.3 Smoothing Noisy Trajectories

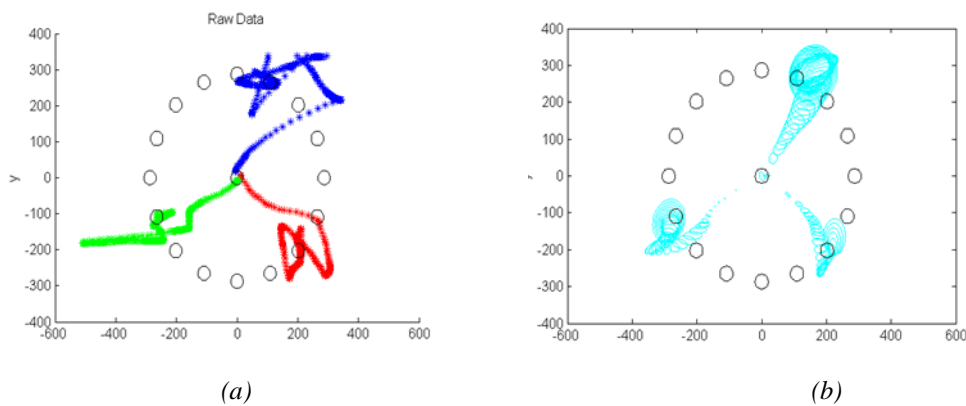
The results of the  $N$  statistical filters applied to determine  $\mathcal{P}(t_k)$  in (1) can be utilised to remove the unintentional perturbations-impairment-related movements as shown in (Ahmad et al, 2016). However, in certain scenarios (e.g. severe perturbations) where it is desirable to maintain 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 (Langdon et al, 2006, Ahmad et al, 2014). 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 (Langdon et al, 2006, Ahmad et al, 2014, 2015 and 2016).

## 3. EXAMPLES: SITUATIONAL AND MOTOR IMPAIRMENTS

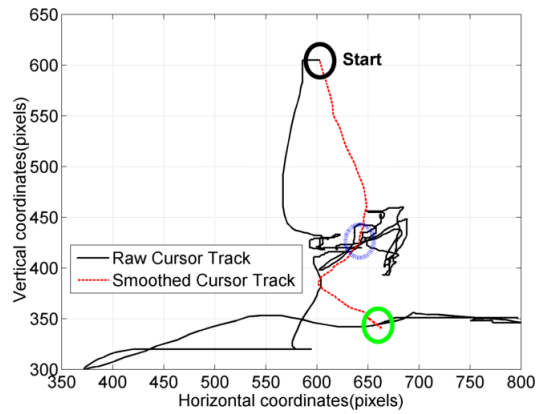
Figure 3 depicts results of utilising an in-vehicle predictive display under varying levels of SIID due to road/driving conditions when the predictive capability is off and on. In the former case, the experiment becomes a conventional task of interacting with an in-car touchscreen where the user has 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.  $\mathbf{m}_k = [x_{t_k} \ y_{t_k} \ z_{t_k}]'$



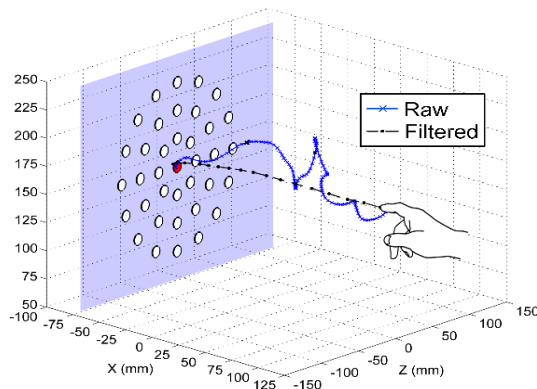
**Figure 3.** Workload scores for interacting with an in-vehicle touchscreen with and without the predictive capability for 20 participants under varying levels of experienced in-vehicle perturbations (Ahmad et al 2016). (a) Minimum perturbations (motorway); (b) Mild-severe perturbations (badly maintained road).



**Figure 4:** Filtering noisy mouse cursor trajectories due to HIID using a particle filter and showing the confidence ellipses (Langdon et al, 2006). (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 (Ahmad et al, 2014). 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 (Ahmad et al, 2014).

at  $t_k$ . Pointing finger observations are then employed by the probabilistic intent predictor to calculate the probabilities  $\mathcal{P}(t_k)$  in (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* (Ahmad et al, 2016). Figure 3 demonstrates that the predictive display system can reduce the 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 6 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.

## 4. CONCLUSIONS

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, originally 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 paper. 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.

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