CrashAlert: Enhancing Peripheral Alertness for Eyes-Busy Mobile Interaction while Walking

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ABSTRACT
Mobile device use while walking, or *eyes-busy mobile interaction*, is a leading cause of life-threatening pedestrian collisions. We introduce CrashAlert, a system that augments mobile devices with a depth camera, to provide distance and location visual cues of obstacles on the user's path. In a realistic environment outside the lab, CrashAlert users improve their handling of potential collisions, dodging and slowing down for simple ones while lifting their head in more complex situations. Qualitative results outline the value of extending users' peripheral awareness in eyes-busy mobile interaction through non-intrusive depth cues, as used in CrashAlert. We present the design features of our system and lessons learned from our evaluation.

ACM Classification: H5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

Keywords: Eyes-busy interaction, obstacle avoidance, texting and walking, walking user interfaces.

INTRODUCTION
Mobile device users habitually multi-task (e.g. texting, web browsing) while walking. Researchers have introduced walking user interfaces (WUIs) [3] to assist mobile usage efficiency with tasks that require significant visual attention or *eyes-busy mobile interaction*. These interfaces include audio feedback [1], enlarged soft buttons [3], two-handed chorded keyboard input [10], and adaptive methods to compensate for extraneous movement [2].

WUIs primarily focus on task efficiency instead of user safety. Eyes-busy mobile interactions limit much of the user's peripheral vision, resulting in users tripping onto curbs, walking into traffic or deviating from their intended path [4,5,9]. In 2008, eyes-busy interaction led to a twofold increase from the previous year, in emergency related accidents [7,6]. This has forced municipalities to consider safety policies that ban mobile device usage while walking [9]. Policy making aside, technological support for safer walking and multi-tasking is unexplored.

We introduce *CrashAlert*, a system aimed at improving safety while on the move. CrashAlert captures and displays information beyond the user's peripheral view using a depth camera attached to a mobile device (Figure 1). The depth camera's field-of-view is orthogonal to that of the eyes-busy operator for increased peripheral awareness. Unlike navigation aids for the visually-impaired which rely on audio or vibro-tactile cues [11,12], CrashAlert extracts a small slice of the depth camera's image, transforms it and places it on a minimal-footprint display on the mobile device. By enhancing the field-of-view users can take simpler corrective actions earlier upon noticing a potential collision. The display also alerts users of obstacles immediately in front of the user through a red alert, prompting users to a more elaborate sorting of the obstacles.

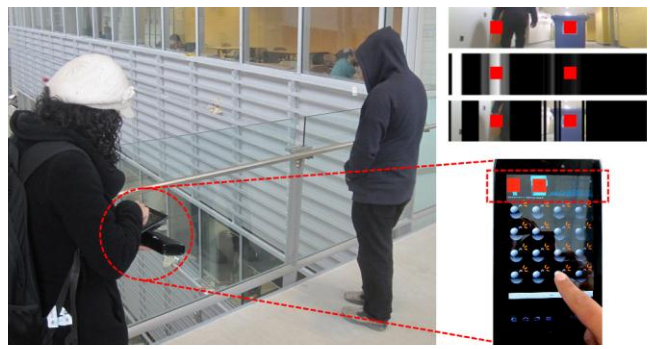

Figure 1 – (left) CrashAlert senses obstacles through a depth camera and informs the user of their positions using various visual transformations. (right) CrashAlert uses limited space on the display and shows close by obstacles with a red alert.

We studied CrashAlert's impact in a collision-prone environment in the 'wild'. Eight participants walked through a cafeteria during busy hours. Our participants easily interpreted our minimal-footprint display and used it to dodge or slow down for obstacles and raised their head in more collision-prone situations. These results were obtained at no cost in performance behavior. Participants also showed unexpected strategies of using CrashAlert such as (a) 'sheltering behind' a pedestrian walking in the same direction, as identified by the red alert, and (b) walking toward the dark. Finally, participants felt safer using CrashAlert.

To our best knowledge CrashAlert is one of the first explorations of a safety aware augmentation of WUIs. Our contribution is threefold: (1) a mobile system, CrashAlert, augmented with a color and depth camera, positioned orthogonally to the user's field-of-view (FoV) for increased peripheral awareness, (2) a set of visualizations based on the camera's depth information, aimed at minimizing screen real-estate and optimizing information about obstacles, and (3) a study of CrashAlert showing improved handling of

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potential collisions and an increased perception of safety, without loss of task performance.

INFORMATIVE FIELD OBSERVATIONS

Our design of CrashAlert was informed through observing pedestrians interact with their mobiles in an indoor university cafeteria. We recorded the holding angle of the device, the number of hands used, the number of steps taken before lifting their heads (to detect on-comers and obstacles), the type of obstacles they most commonly avoided, patterns in walking speed and how many steps they took while typing.

When walking, people handle possible collisions by slowing down or dodging them, lifting up their heads, full stops or ultimately a bump. Each of these approaches with a higher cost for the person. Peripheral information allows people to notice possible obstacles early on and take simpler corrective actions (slowdown/dodge). As their walking continues, the obstacle is reevaluated and, if needed, further corrective actions are taken (heads-up). Limited peripheral vision means that obstacles are noticed later on, restricting the suitable corrective actions to higher cost ones (full stop or bump). A WUI supporting safer walking should therefore prompt users to take simpler corrective reactions early on by **encouraging dodges (R1)**, and **alerting on imminent collisions (R2)**.

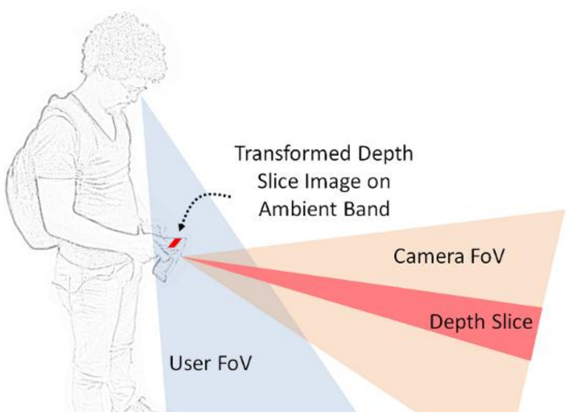

Figure 2 – A depth camera extends the users' limited peripherals awareness.

CRASHALERT

CrashAlert (Figure 2) is a system designed to let users act safely in eyes-busy interaction. CrashAlert has two main components: an ambient visual band and visual alerts for near-by objects. Our system uses a depth and a regular camera to capture a region in front of the user but outside their field-of-view (FoV). We extract only a small slice of the camera's image and process this to present obstacle positions and distances on the small footprint ambient band. The band conveys a glance-able representation of the elements in front of the user and outside their FoV (R1). The visual alerts are generated from the depth image for objects that are as close as 2 meters away from the user. Their appearance (a bright red square in the position of collision, Fig 3) is easily noticeable by the user, prompting them to raise their head to better cope with obstacles (R2). We also considered tactile feedback but discarded this in our implementation to isolate the benefits of a small visual footprint from other feedback methods.

We generated different visualizations for the ambient band through a design workshop with eight participants. Participants interacted with 11 different visualizations. Figure 3 presents the three most preferred ambient bands: a) color image, b) depth image, and c) masked image. The *color* image is a slice of the color picture taken with the color camera (figure 3a). The *depth* image is obtained by applying a binary threshold to the depth capture for a fixed distance (5 meters) and assigning the max value of each column to all of its pixels (figure 3b). The *masked* image uses the depth image (from figure 3b) as a mask on the color image; this way it shows the full color version of the closest objects on a black background (figure 3c). All bands presented a red alert when the obstacle was 2 meters close.

Figure 4 –Ambient band visualizations based on given scene (best seen in color).

Implementation Details

Hardware. CrashAlert is a prototype that operated on an Acer A100 7'' tablet computer, a laptop computer, and a Microsoft Kinect (see Figure 3). The laptop is carried in a backpack together with a 12 volt battery to power the Kinect in a mobile setting. The laptop receives images from the Kinect via USB, processes and transforms them, and sends them to the tablet via Bluetooth. The tablet receives images at a rate of approximately 10-11 frames per second. *Software.* The laptop runs a .NET C# application which interfaces with the Kinect, processes the images with OpenCV, and communicates them over Bluetooth. The tablet application is an Android 2.3.3 application.

EVALUATION AND USER FEEDBACK

Our experiment was designed to observe participants' safety behaviors using CrashAlert. We recruited eight university students, from various disciplines, who habitually text and walk (6 male, 2 female, mean age of 25.5 years). All participants text while walking but agreed that such practice is dangerous. On average, our participants reported having a dozen collisions over the last year.

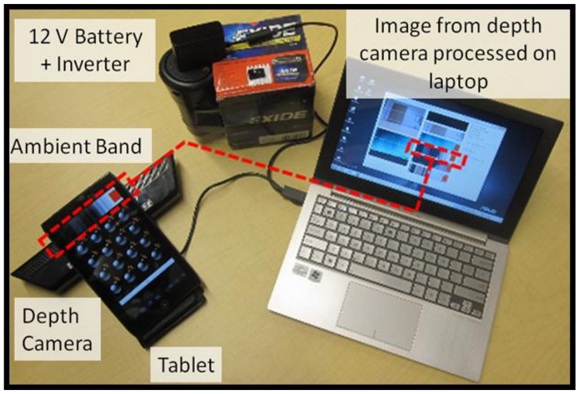

Figure 3 -- Hardware components in CrashAlert.

We designed a within-subjects experiment in which participants were exposed to four conditions: (1) None or No feedback (None), (2) Camera alone (CA), (3) Depth Image (DI) and (4) Image with Mask (IM). Conditions were counter-balanced with a Latin-square experimental design. The camera was fixed at a 0º angle and participants were asked to hold the tablet in a natural way. The depth slice covered the middle-low 2/5 of the depth and normal images.

Task and Procedure

We asked participants to play a whack-the-mole game while walking through the university cafeteria. Each trip (or trial) consisted of starting the walk at the near-by bookstore and looping around the entire food court (180 meters). Participants were asked to walk as normally as possible while playing the game. Their objective was to tap on as many moles as possible during their trajectory. Participants were asked to naturally avoid collisions with people and obstacles. We ensured that participants would face *at least* four collisions during each trial. This was achieved by asking an 'actor', unknown to the participant to provoke potential collisions. The 'actor' would cut the participants' path orthogonally, would stop right in front of them, would come toward them at a fast pace, or would walk beside them but then immediately swerve in their lane. None of our participants suspected the presence of the 'actor'. Participants also faced obstacles from other people and objects in the cafeteria. The experimenter recorded participants' behavior during any potential collision.

We captured the user's total walking time, the number of moles they 'hit', as well as the number of times they performed a 'dodge/slow down', a 'heads-up', a 'full stop', and a 'bump'. Each experiment lasted roughly half an hour. Each condition was done twice, resulting in 8 participants x 4 conditions x 2 trials = 64 trials in total. We also interviewed the participants between trials and at the end of the experiment, and collected data (5-step likert scale) about their perceived safety, efficiency, alertness, walking speed, understandability and glance-ability of each condition. If a mole was not hit within 2.5 secs we recorded an error and the mole was shown as being destroyed.

Participants wore the backpack containing the battery pack to which the Kinect was connected. They were first explained the task and were briefly explained the visualizations. We did not inform them of the planned collisions and asked them to behave naturally while trying to hit moles in the game as efficiently as possible. Participants walked through the cafeteria as per the assigned path.

Results and Discussion

Each trial lasted 130.5 seconds on average (*sd* = 20.8) with an average number of 246.25 moles whacked per trial (*sd* = 42.4), and an average error rate of 0.64% (moles missed, *sd* = 1.37%). Moreover, participants whacked moles at an average rate of 1.91 moles/second (*sd* = 0.04). There were no significant differences between conditions on the number of moles hit or error rate. Therefore the wide spread in the number of moles per trial is explained by the wide spread in completion time. For the total 64 trials we registered 721 instances of possible collisions with an average of 11.26 (*sd* = 2.96) per trail (only 4 were caused by the actor) and 180.25 (*sd* = 8.84) per condition.

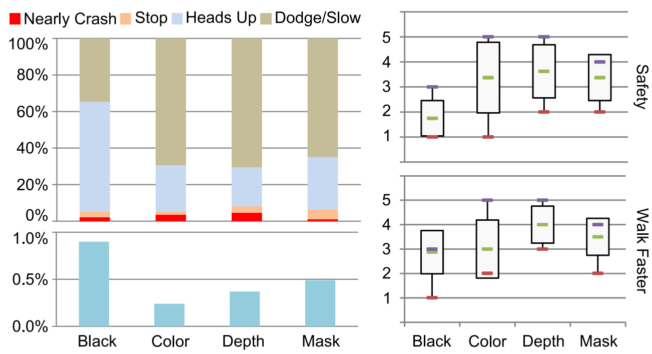

Figure 5 – (left-top) User corrective actions broken down into % of the total. (left-bottom) No significant difference in error rates among techniques. (right) User rankings for their perception of Safety and Walking Speed.

We used the univariate ANOVA test and the Bonferroni correction for post-hoc pair-wise tests for our analysis. Figure 5 shows an overview of the results. Figure 5-left-top shows the percentage distribution of collision handling maneuvers (dodge/slow-down, heads up, stop before crash, near crashes) for each condition. Results showed a main effect of feedback style on the number of dodge/slow-downs ($F_{3,21}$ = 3.694, p < 0.03) and head ups ($F_{3,21}$ = 10.553, p < 0.01). Post-hoc analysis showed differences only between the no-feedback condition and all the others, but not between the various visualizations. These results show that with CrashAlert participants avoided more obstacles by dodging rather than by heads up. Moreover, this better handling came at no cost in playing the game (no significant difference in error rate – figure 5-left-bottom). Finally, there was no significant effect of feedback style on completion time ($F_{3,21}$ = 0.7, p = 0.4). These results show that CrashAlert induced simpler corrective actions (dodge/slow) to possible collisions, providing space for other more complex corrections later on, and thus providing for safer walking.

For the qualitative ratings we used the Friedman χ^2 test. Results (figure 5-right) showed that with CrashAlert, participants felt safer ($\chi^2(3) = 9$, $p = 0.029$) and had a perception of walking faster ($\chi^2(3) = 10.385$, $p = 0.016$). There were no main effects on the other factors.

We interviewed each participant after each condition and had a longer debriefing after the whole experiment. We coded their answers (19 tags) into 4 topics: abstraction, navigation, alerts, and technical improvements. We discuss only the first three. In terms of the *abstraction* level, participants said that even though the color and the masked images provide higher levels of detail, they were harder to read, requiring more attention and generating more stress when executing the task (even though we did not find any significant impact in performance); for example P8 said "*I have to check the [color] image much more and longer*". In contrast, the depth images were found easier to read "at a glance"; for example P7 indicated that "*[with the depth image] I can see the [thin] veranda which I couldn't in the color image*". Moreover, participants reported depth images as falling into the background to the point some were not sure whether they used them consciously.

Participants talked about the different ways that CrashAlert enhances their current *navigational* senses (sound, peripheral view and knowledge of the environment) beyond simply alerting about obstacles and potential collisions: (1) allows participants to walk toward the dark regions shown on the ambient band and (2) appropriate the alert. Some participants found it useful to simply relax and follow the darker areas of the depth images, as they trusted that these areas would not have obstacles. In a different situation, when walking through a narrow and crowded corridor, a participant knew the person in front of her (shown with an alert due to proximity) was walking in the same direction and so she decided to follow the position of the alert to way-find through the crowd.

Finally, participants also noted that a system based only on depth alerts (no color, masked, or depth images) would already be an advantage compared to having nothing. Moreover, participants indicated the need for different *alert types*. One such type is alerts based on direction and speed; for example, participant 1 said "*I couldn't tell whether people where coming toward me or moving further away*". Another type of alert would be based on the type of object (static or moving object) and their related hazard estimation; for example P3 noted "*[I would like to see] a significance level indication of obstacles like how much danger if collision occurs*", and P5 said "*perhaps I could be alerted about different objects in different ways… moving people and static chairs require me to take action differently considering time and predictability*".

Lessons Learned

We observed at least three main benefits of CrashAlert:

- Depth and color images orthogonal to the user's FoV can facilitate safe navigation (dodging or heads-up);
- Only a small slice of the images are needed;
- Alerts based on depth information are useful.

Limitations

This initial exploration was limited by a low image rate (10-11 fps), a bulky hardware set-up, and naïve detection of obstacles (distance-based). However limited, our system demonstrated the value of considering safer WUIs. Future work should investigate alternative visualizations, varying alert styles, such as a growing or shrinking box based on distance and speed, other feedback modalities, impact on complex tasks, dynamic selection of image slice, scene analysis and object recognition (type, direction, speed, etc).

CONCLUSIONS

We presented CrashAlert, a mobile device augmented with a depth sensing camera that shows users out-of-periphery objects in their path while walking. CrashAlert shows salient information such as distance and position about potential obstacles. The information is displayed on a minimal footprint ambient band on top of the device's display. Study results show that users take simpler corrective actions early on upon noticing an obstacle felt safer with our system and used it to help navigate around the environment. There was also no negative impact on performance, showing that even minimal environment information outside the user's periphery can provide for safer usage of mobiles while walking.

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