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Situated Analytics: Demonstrating immersive analytical tools with Augmented Reality

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ABSTRACT

This paper introduces the use of Augmented Reality as an immersive analytical tool in the physical world. We present Situated Analytics, a novel combination of real-time interaction and visualization techniques that allows exploration and analysis of information about objects in the user's physical environment. Situated Analytics presents both situated and abstract summary and contextual information to a user. We conducted a user study to evaluate its use in three shopping analytics tasks, comparing the use of a Situated Analytics prototype with manual analysis. The results showed that users preferred the Situated Analytics prototype over the manual method, and that tasks were performed more quickly and accurately using the prototype.

1. Introduction

In this paper, we present real-time interaction techniques, which we called Situated Analytics (SA) [1]. SA draws on two research domains—Visual Analytics (VA) and Augmented Reality (AR)—to provide analytical reasoning in the physical space [2]. VA is a multidisciplinary field covering analytical reasoning techniques while AR enriches the physical world view with contextual information in real-time [3,4]. SA combines VA analytical techniques with AR techniques for in situ projection of information onto the physical space.

We consider the question of how SA can be beneficial for data exploration and information comprehension. We believe SA can enhance decision making in three ways: clearer information presentation by directly associating information with the relevant physical objects, more natural interaction for information exploration by touching and manipulating physical objects, and more sophisticated information analysis providing contextual and overall information.

Fig. 1 demonstrates SA within the context of a shopping task. SA enables user exploration and interaction with information in novel ways. In Fig. 1a, a user explores a product's overall information, presented to them as a virtual annotation overlayed on the top of the physical box. Information of interest is highlighted—for example, if the user is searching for Australian-made products, the Australian logo can be highlighted. Fig. 1b shows a user interacting with the physical object to explore more information (Details-on-Demand). The user can explore information, such as the ingredients printed on the product's box, and the SA system will display detailed visual analytical information based on the product's ingredients (for example, the percentage of the user's daily recommended intake (RDI) for a nutritional category such as sugar or fat that the product contains). SA also allows a user to analyze and compare information between products (seen in Fig. 1c). As an example, when a user selects two products and places them side-by-side, the SA system presents a comparison of the two products to the user.

To create the SA system described in Fig. 1, a number of challenges need to be addressed in order to merge VA and AR techniques. Some of the open research questions include:

- How should the visual presentation of the information be linked to the objects in the physical space [5]?
- What are the best ways to represent the abstract data (categorical, rank, numeric, temporal, spatial etc.) associated with the physical objects [6]?
- How should abstract relationships, such as connectivity or ranking, between physical objects be shown to the user?

Within this investigation we developed and evaluated a shopping application that demonstrates how SA can support users in the manipulation of complex data mapped to physical artifacts

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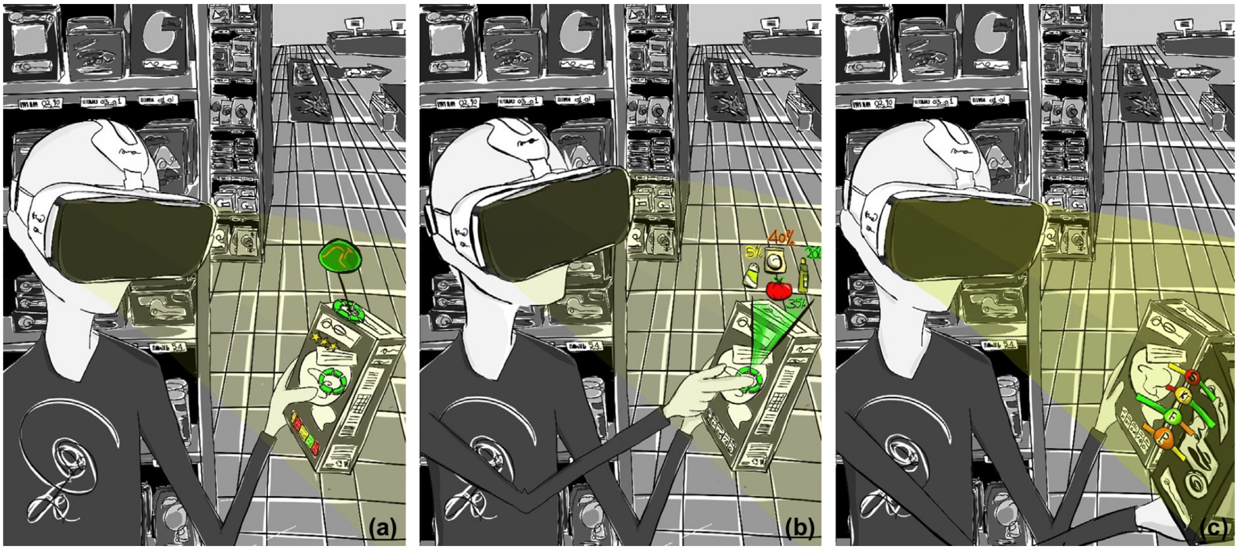

Fig. 1. Situated Analytics allows users to visually interact with information in Augmented Reality. (a) Users can view the attached information, (b) interact with physical objects to explore more information, (c) and view/compare the information associated multiple physical objects.

with AR. The evaluation of our prototype explores possible directions to address the mentioned challenges. When reasoning with location based multidimensional data, we believe SA is a method that fulfils the needs for enhancing its approachability, while also improving its speed.

We present SA, a novel method of interactive exploration for multidimensional data that is designed for use in AR enhanced applications. This work is built on White and Feiner's work for visualization in AR [6]. They presented different visual representations for multi-dimensional data. While the data in White and Feiner's SiteLens system are multi-dimensional, their visualizations do not support real time analytics and interactive manipulations of the analytics. They provided information based on the situation, but to apply situated analytics we need to present multi-level data with different data types (multidimensional, temporal, tree, etc.) [7]. We need to provide interaction tools that allow users to manipulate the data attached to the physical space.

We applied a number of techniques on a set of visual representations for displaying results from multi-dimensional data queries for product selection contexts (shopping tasks). These techniques are filter (see Fig. 2), find (see Fig. 3), and rank (see Fig. 4), of co-located physical objects.

In this paper we experimentally investigate the usefulness of SA and explore the trade-offs between it and manual information analysis. We are also interested in exploring real world tasks to support users in decision making through the use of AR-presented multi-dimensional data, and improving users' abilities to analyze information. We present the results of a user evaluation that focused on the visual representation and interaction aspects of the situated analytics system, where the users were asked to select, rank and filter grocery products based on their price, ingredients and nutritional benefits.

In the remainder of this paper discusses the related work of AR, Visualization, and VA. Section 3 details our SA approach, including our interaction and visual representations. Following this, our user evaluation, and results thereof, are presented. The paper finishes with set of concluding remarks.

Fig. 2. Example of Filtering visual representation, by highlighting the product of choice with a green enclosing rectangle while hiding the unwanted products with a semi-transparent black object with a red "x" overlay. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Fig. 3. Example of Finding visual representation, by highlighting the resulted product with a green frame, and the other products blocked with visual green navigation arrows to guide the user to the correct product. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

2. Related work

AR overlays physical objects with computer generated information [8]. This information merged with the real scene gives AR the potential to be one of the main display spaces for supporting immersive analytics applications [1,9,10]. Providing a user with a spatial grouping of information AR can enhance user understanding of information; however, the grouping and

Fig. 4. Example of Ranking visual representation, by employing the saliency cues of size and color to reflect the ranking values. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

presentation of information is inherently limited by the placement and layout of the physical objects within the environment, causing a reduction in the visualization layout zones [11].

A growing field is VA, which has been developing interactive visualization approaches to address existing challenges with big data [12]. VA provides tools that allow users to reveal the relationships and patterns within data [7], improving on traditional interactive visualization tools. VA differs from traditional information visualization primarily through its emphasis on open-ended interactive exploration of data, combined with sophisticated analytics. One of the main advantages of VA is the reduction of the overall data presentation space, and the use of interaction tools that allow users to explore data based on the user's own perspective. We believe that using VA concepts for data exploration, combined with AR as a display space, provides a promising solution for achieving goals of the situated analytical reasoning.

2.1. AR visualization

Through the last decade, research has explored different visualization techniques for incorporating information within AR environments [13]. Kalkofen et al. [14] classified the AR visualization approaches into three main categories: data integration, scene manipulation and context driven. Data integration techniques enhance the blending of the virtual information with the real scene [14–16]. Scene manipulation techniques manipulate the real scene to augment information, for example the relocation of physical objects [17], color corrections [18], and diminished reality techniques [19]. Context driven techniques alter the visual presentation of information based on the context information [6]. Unprepared environments, tracking, and registering virtual information, remain an open research question. Another research challenge remains with the limitations of current AR display technologies [20], which differ from traditional displays.

2.2. AR information presentation

Interest in AR-based information visualizations has surged in recent years, due to the increased stability and ubiquity of AR-capable devices, including mobile phones, tablets, and wearable devices. One of the main challenges facing information visualization in AR is the registration of large data sets within the AR scene. Previous work has attempted to solve this challenge using combinations of three main approaches: complexity reduction, layout optimization, and interaction techniques. Both complexity reduction and layout optimization attempt to optimize data representations, whereas interaction techniques provide tools for a user to explore the structured data on demand (DoD).

Complexity reduction approaches filter the amount of information to reduce the size of the presented data. The filtering techniques can be based on spatial location, user profiles, or a combination of multiple attributes. One of the common filters used in AR is the location of the user in the real world. Occlusion and being able to view items behind the objects creating the occlusion are powerful cues for the user to understand location based visualization information [21]. Julier et al. [22] have introduced a filtering technique that can visualize the data based on users' locations and intentions. Users of their system undertake tasks with information that varies based on their status in the task and their location in the real world. Livingston et al. [23] used the users location and tasks to visualize the occluded layers of infrastructure of a building. Their research uses different visual representations based on the distance between the user and the physical building. User profile filtering is one of the most common filtering approaches in information visualization. This type of filtering has been introduced to the AR community by Hervás et al. [24], who used the user's profile to filter the data for an AR assistant application. Filtering approaches can use combinations of one or more filters. For example, Luna et al. [25] used both user location, and point of interest, as filters for data reduction.

Layout optimization approaches are used to enhance the presented information's layout within the available viewing display. These techniques vary based on the display types, and inherit the challenges associated with the display type used. Layout optimization has been commonly used for visualization of text labeling within AR systems. Azuma and Furmanski [11] proposed a view management approach for text annotation arrangement. Their system aligns the text labels based on the viewpoint. Later, Bell et al. presented a layout management approach for text and images. The advantage of that approach is that the representation size changes based on the depth of the information with respect to the view, which enhances the perception [26]. Moreover, Bell's technique shows a potential of combining filtering with layout approach. Another approach for layout management has been proposed by Tatzgern et al. [27], who laid out the presented annotation into 3D space instead of 2D space, thus reducing the representation's cluttering.

2.3. AR information interaction

Over the last decade, interest in improved interaction techniques for big, multidimensional data has grown. Interaction techniques have been used in AR to address shortages of display space within the AR view. The Touring machine was one of the earlier approaches that has used interaction techniques to explore details-on-demand (DoD) [28]. In this example, a head worn display was employed, attached to a wearable computer, to highlight key points of interest. The system supported interactions on a hand-held tablet computer to navigate between a numbers of hyperlinks describing information about the Columbia University's campus. This approach was one of the earlier approaches that worked with tree-structured data. However, this approach cannot work with other data types, as they used a static relationship between the data nodes (spatial location and hyperlinks). Another approach, posited by Walsh and Thomas [29], involved the development of an outdoor wearable AR visualization system for environmental corrosion data. The goal of their system was to represent information for large scale structures such bridges, while maintaining uncluttered scenes through data reduction. They used a wireless sensor as the source of the presented data.

Although approaches have been taken to address the difficulty of presenting multidimensional data within AR, it represents a continual challenge facing AR information visualization. This is due to the system needing to represent the relationship between the data nodes, and also to support data exploration criteria. White et al. [30] presented one of the earlier approaches to visualize multidimensional information in AR. Their approach allows users to query through pre-stored data. They used tangible interaction tool for information interaction. Although their system compares the query and compares within the information attached to each physical object, there is no support for comparisons between information attached to different physical objects. Zollmann et al. [31] presented an approach that can visualize data nodes and the relationship between them, but their system is restrained by the requirement of having only static, pre-defined relationships between the data nodes. With the rapid growth in generated information, multidimensional data now represent a key challenge facing AR browsing tools [32,33]. The main gap in the existing approaches is that they are filtering the data, which can lead to data masking. This data masking reduces the efficiency of analytical interactions, such as searching, comparing, and clustering. Recently, Eduardo et al. [34] proposed interactive visualization approaches for AR monitoring. Their approach shows a potential benefit for the analytical reasoning visualization tools.

2.4. Analytics

The amount and complexity of data available to researchers in the physical-, life- and social-sciences as well decision-makers in business and government is growing exponentially. Several overlapping research fields support the analysis of such Big Data, in particular: information visualization, scientific visualization, machine learning, data mining and data science. *Visual Analytics*—introduced a decade ago as "*the science of analytical reasoning facilitated by interactive visual interfaces*" [2,12]—can be seen as the combination of these fields in recognition of the need for a holistic approach. Visual Analytics techniques and tools, such as Tableau, are now widely used in business, science, government and for personal information management.

The above definition for Visual Analytics is agnostic of the actual interface devices employed by Visual Analytics tools. However visual analysis tools are almost universally designed for use on a standard desktop computer: a single average-sized display, keyboard and mouse. A recent direction in Visual Analytics research is Situated and Immersive Analytics [1,9,10]. This redresses this focus by examining how best to support Visual Analytics on immersive visualization platforms like the CAVE or VR head-mounted displays.

We believe that using VA concepts for data exploration, combined with AR as a display space, provides a promising solution for achieving goals of situated analytics.

In summary, the two existing solutions for multidimensional visualization in AR are: *data filtering* and *interactive exploration tools*. However, these filtering techniques lead to masking of large quantities of data, rendering them incompatible for many tasks, including decision-making. Moreover, the existing visualization interaction tools for AR rely on static data relationships for navigation, such as location, time, or type. These tools provide the users only a limited number of predefined analytical perspectives for the presented data. Previous investigations have applied analytic techniques to enhance the layout management and content exploration.

In our approaches we applied the analytics to the user interaction, allowing users to view the information from their own perspective. In order to illustrate the pragmatic effectiveness of our approaches, we targeted one domain that has received notable interest: shopping.[1] The main challenge of the shopping context is that the data type is multidimensional data; additionally, there are no predefined filtering approaches that can be applied, as the shopping experiences significantly change between consumers based on their behavior. Zhu et al. [35] proposed an in-store, e-commerce, context-based system. They employed AR on a handheld tablet PC to improve the user's shopping experience. Although this approach works with multivariate data, their approach introduces dependencies between the data based on a predefined clustering. This approach limits the user's query options. Another approach was introduced by Kahl et al. [36], their approach employed RFID and touch screens to guide users in the shopping based on their predetermined shopping lists, and the supermarket map.

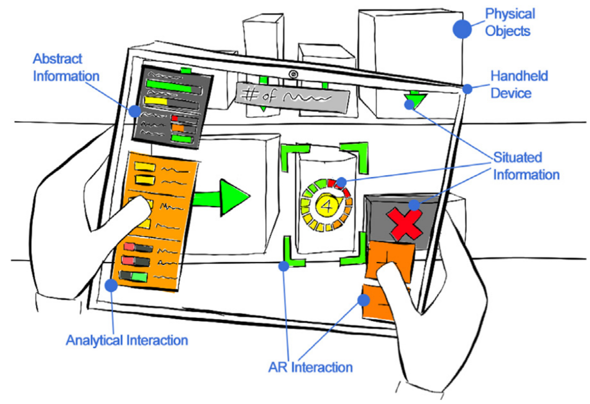

Fig. 5. Situated Analytics system interaction and visual representation. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

3. Situated analytics

The main objective of situated analytics (SA) is to help users make informed decisions [9]. SA affords users the ability to perform analytical tasks while remaining immersed within the physical world. Users can interact with physical objects, as well as information virtually attached to each object. These interactions allow a user to perform complex queries in the context of a physical object, and visualize the outcome of the applied query.

In this section we present our novel SA concept. The concept is illustrated using AR via a handheld tablet display, which augments the user's view of the physical world with additional information. However, our approach is not limited to video see-through handheld displays, and can also be applied using both optical and video see-through head mounted displays (HMD). Fig. 5 illustrates the four main UI components of the situated analytics model, which are: *analytical interactions*, *AR interaction*, *presentation of abstract information*, and *presentation of situated information*.

3.1. Interaction

The situated interaction tools are one of the key differences between situated analytics and the traditional AR interactive visualization. SA uses two main interaction types: *analytical interaction* and *AR interaction*.

[1] http://www.research.ibm.com/articles/augmented-reality.shtml.

3.1.1. Analytical interactions

Analytical interactions allow users to interact with the information associated with physical objects. Users can apply analytical queries, such as filtering, sorting, and comparing, on this associated information. Our approach is to bind the analytical interaction controls to high-level constructs that define a range of dimensions in the information space. We employ three forms of controls: toggle buttons, radio buttons, and sliders. Toggle buttons give the ability to perform binary queries, for example to analyze the presented data after filtering or masking some attributes. Radio buttons are employed in the case of orthogonal relationships, where only one option from several options can be made. Sliders are employed to allow users to enter a ratio value between two extremes, such as filtering or sorting values. These UI controls of the analytical interaction strongly depend on the applied application. For this reason, we believe that binds between analytical interactions and UI components will be application specific.

3.1.2. AR interactions

AR interactions allow users to interact with the physical objects in the context of a query, such as selection or deselection of an object, as appose to interacting with a physical input device [37]. This interaction allows users to analyze the information based on the physical context. Fig. 5 depicts a user selecting a physical object, the user highlights the physical object and presses the "+" button to select the physical objects. To deselect a physical object, the user highlights the object and presses the button "−". We use a ray-casting technique between the tablet's camera and the physical object to select the object. The ray is defined as perpendicular and centered from the image plane defined in the AR view. This technique allows users to easily select an object by aiming the camera at the object, and pressing the select or deselect button. These buttons are placed in a comfortable to use position and in a reachable area under a user's thumbs.

3.2. Visual representation

The SA visual representation is divided into two main categories: *abstract information representation* and *situated information representation*.

3.2.1. Abstract information

The abstract information represents the overall information. The appearance of this information is based on the outcome of scene queries. It can show the summary information, and the outcome of the analytical interaction between physical objects. For both situated and abstract information, we use the saliency cues of size, color, and orientation to encode information. A problem with SA is the default visualization is focused on the objects in the context. This focused information leads to the masking of the overview. We used the abstract information to solve this challenge. Fig. 5 depicts the abstract information panel. We used health bars with dynamic size and color. A bar's size and color changes based on the user's status and queries. These bars are affected by both the analytical interaction and the AR interaction.

3.2.2. Situated information

Situated information is used to register the information associated with physical objects. The location and the appearance of this information changes based on the physical object's location and is based on the information associated with them. We investigated ways to represent the results from the following three different kinds of queries: *filtering*, *finding*, and *ranking*. Our goal was to apply visualizations that were informative, easy to understand and intuitive.

For filtering we developed a visual representation that partially masked the physical objects with a transparent overlay. Fig. 2 shows a visual representation method for filtering. Physical objects of interest are highlighted with a green enclosing rectangle and the unwanted physical objects are hidden with a semi-transparent black mask and overlaid with a red "X". Additionally, this technique could be modified for situated color-coded clustering, by modifying the visualization input to be numerical rather than a truth value; changes to the visualization's size and color would then be based on the numerical value.

For finding we highlighted the target with a green frame and used the other physical objects for navigational guidance to the target. The target is calculated based on the parameters entered by users through the analytical interaction. Fig. 3 depicts our visual representation for a finding query. We assume that the spatial relationship between the objects is known. This spatial relation can be calculated during operation through the AR tracking technology for all the physical objects viewed and recognized.

Ranking is used to inform the user of a sorted subset of physical objects. Users can select and deselect physical objects to involve them in the ranking process. This AR interaction leads to a different ranking output. As the physical objects are selected, they are added to the set of objects to be ranked, and the visual representation is updated interactively. The user may deselect objects to remove them from the set. Fig. 4 depicts one of the visualization options we have developed. Our ranking visualization approach employs the saliency cues of size and color to reflect the sorting value. The visual representation's algorithm changes the cue size based on the ranking value of the physical object (Vs_i). The size value is change within a range between zero to the maximum scale factor $(Sx_{max}, Sy_{max}, Sz_{max})$. This factor value is a ratio determined from the physical object's dimensions:

$$Size(x, y, z)_i = \left(\left(Sx_{max}/Vs_i\right), Sy_{max}, \left(Sz_{max}/Vsi\right)\right) \quad (1)$$

The color of the visualization is a mixing value between red and green, as green has the highest nutrition value, passing through yellow, with red the lowest value. Color can be used to overlay extra information with size. Fig. 4 shows the use of both size and color to present nutrition information, where size is used to represent the ranking value and color is used to represent the nutrition value:

$$Color(x, y, z, a)_i = \left(\left(Vc_i/n\right), 1 - \left(Vc_i/n\right), 0, 1\right) \quad (2)$$

When merging VA concepts into an AR domain, we observe that the traditional, open-ended Shneiderman's information mantra of *overview first, zoom and filter, then details on demand* [7] does not readily apply to SA. Instead, we propose that, for SA applications, the information mantra be modified to become: *analyze first*, *highlight (show the important)*, *zoom*, *filter and further analysis*, and finally, *details on demand*. We found that exploration for the SA to be almost opposite the traditional mindset: *details* first, *analysis*, then *context-on-demand*.

4. Situated analytics for shopping scenario

Of the many areas SA might apply, we selected shopping because the grocery shopper has a wealth of information directly and indirectly available about products on the shelf: price, ingredients, nutritional information, information about the manufacturer, origins of ingredients and sustainability of the manufacturing processes, and comments about the product in social media. These shopper queries were a good option to evaluate our approaches. Moreover, in this domain we used a set of nutrition equations, which evaluated the analytical part of the system.

Based on the design of our situated analytics system, we have developed a prototype situated analytics tool for grocery selection during shopping. While a number of AR shopping applications have been previously developed, our intent is to explore the effectiveness and usability of a tool that provides complex nutritional and budget information. The goal of our investigation is not to produce an actual shopping application, but to use the shopping context as a vehicle to validate the concept of SA in a context that is complex enough to require sophisticated analytics for the end user.

Fig. 6 shows a screenshot from the tool we have created. It shows the abstract and the situated information representations based on user interaction. As previously mentioned, the salient cues (size, color, text and texture) are used in both techniques to convey the information's meaning. In our application the abstract information represents the user's status from the recommended daily intake. The size and the color of these bars dynamically change upon the user selecting and deselecting products from the shelf. The abstract information is presented in the top left of the screen, which also shows the total number of products in the user's cart.

The analytics interaction for this application allows the user to interact with complex nutrition equations, by changing the input parameters. The analytical interaction panel allows the user to assign the shopping budget value, the shopping purpose (daily, weekly or monthly), and the serving amount for this product.

The abstract information provides the user a global context, such as the total intake, the content percentage of the health meal. This abstract information changes dynamically with the user interaction. The situated visualization is augmented on the product faces. After the inclusion of a number of products, a set of products is no longer recommended, and this is indicated by a large red "X" blocking sign.

Fig. 6. The SA approach on shopping context application.

4.1. Interaction for shopping scenario

The analytical interaction of this application allows the user to interact with complex nutrition equations. Users can manipulate the parameters for complex ranking functions, to search for options, alternates, and relationships between products. In this tool we used three nutrition algorithms that are affected by user interaction, and are depicted in the visual representation. We used the following three nutrition equations: Point system algorithms for food and targets [38], Star guidance program for the general foods and beverages [39], and the Healthy eating plate.[2] These three equations are used to reflect different nutrition possibilities. The Point system equation dynamically changes based on user profile, product information, analytical interaction, and AR interaction. The Star system dynamically changes based on product information and analytical interaction. Finally the health plate is affected by the AR interaction.

The Point system [39] calculates a healthy nutrition allowance based on a user's profile. The interaction with the Point system attributes is provided through radio buttons in the analytical interaction panel. This panel allows changing the shopping frequency (daily, weekly, monthly). When products are virtually select or deselect from the shelf, these selections will affect the calculation of the remaining allowance. We used the Point system equations to calculate the point system for each product on the shelf:

$$P(c, f, r) = \left(\frac{c}{50} + \frac{f}{12} + \frac{\min\{r, 4\}}{5} \right) \tag{3}$$

Where P is the number of points, c is the amount of energy in calories, f is the amount of fat in grams, and $\min\{r, 4\}$ is the minimum dietary amount of fiber or the constant 4.

We used the points allowance for each use, to calculate the total points budget for each user:

$$PTD(x) = (W_x{*}0.1) + \sum_{i=1}^{5} Px_i$$
$$PTW(x) = PTD_x{*}7 + 35 \tag{4}$$

where x is the user, PTD is daily points, PTW is weekly points, W is the user's weight, i is the categories points (gender, age, tall, physical effort, and extra).

The Star system [39] is used to reflect the health factor for products based on their ingredients. We alter the star calculation to reflect a health factor from 0 to 100 instead of the original number of stars from 1 to 3. The interaction with the Star system attributes is provided through increase and decrease buttons in the analytical interaction to change the serving amounts, as follows:

$$Star(x) = \sum_{i=1}^{8} Sx_i{*}sv \tag{5}$$

where $Star$ is the star value, x is the product, i is the ingredient point (trans-fat, saturated fat, cholesterol, sugar, sodium, fibre, vitamins, and whole grain) and sv is the serving amount.

The healthy plate is a formula to calculate the kilojoule meal allowance from the total kilojoule allowance. This formula is strongly affected by the AR interaction, where selecting /deselecting changes the remaining kilojoule allowance. The user may use the analytical interaction to change the meal type, for example breakfast or dinner:

$$m_{kj} = X_{kj}{*}mF \tag{6}$$

Where m_{kj} is the total Kilojoule allowance for the meal, X_{kj} is the daily intake total Kilojoule per user, and mF is the meal factor.

4.2. Visual representations for shopping scenario

We used both situated and abstract information in the shopping tool. Situated information is used to visualize the result of the user's interaction with the pre-sorted nutrition functions. Fig. 5 shows the situated and abstract visual representations. Situated visualization is used to represent the point value on each product package. The circular health bars reflect the star value. This health bar reflects values from 0-red to 100-green. The "X" blocking signs

[2] http://www.hsph.harvard.edu/nutritionsource/healthy-eating-plate/.

are used to hide products. This sign reflect the incompatibility of product, and also that this product cannot be selected. Fig. 7 shows another visual representation that has been used for details on demand (DoD), When hold the product package and start to interact with it, they can explore more detailed information.

The abstract information is to represent the overall information. Health bars are used to reflect the total and status of the user's points and calories. These bars also used to reflect the plate contents' status based on the Health plate formula (see Fig. 6).

5. User study

We conducted a user study to validate portions of the proposed situated analytics paradigm. The aim of the user study was to evaluate the benefit of an immersive AR analytical system for enhancing a user's understanding of information. The focus of this study was on the AR interactions and situated information aspects of the system. Through the study we compared the error and completion time for shopping tasks between the situated analytics approach and the manual approach. Participants were asked to complete three shopping tasks: Filter, Find, and Rank, using two approaches (situated analytics, and manual). For all the tasks we measured the time and the error. *Incorrect error* is when users selected the wrong product and *omission error* is when they missed selection of the product.

5.1. Equipment

We conducted the study experiments on a mockup shopping environment. We used two standard bookshelves to serve as shopping shelves. One shelf was used for AR tasks (situated analytics approach), and the other for the manual tasks (see Fig. 8). Standard products from a local supermarket were used to complete three tasks. We chose eight different products on each shelf, as we believe customers in the supermarket shopping context would not commonly compare more that eight similar products whilst shopping. We also aimed to keep the manual task's expected duration to within a reasonable time.

A defused photographic lighting system was installed for the AR shelf to enhance the tracking performance, as we are not investigating AR tracking technologies in this study. To optimize tracking performance, the products on the AR shelf were slightly separated. The prototype application was developed with Vuforia[3] and Unity.[4] A Sony Xperia tablet was used to present the situated analytics application and was also used to measure the completion time in both the AR and manual tasks. The task started when the users pressed the task button on the tablet and ended after they pressed the end button.

5.2. Study design

The shopping experimental task was a 3 $\times$ 2 $\times$ 2 repeated measures design. The examined independent variables were *tasks* (Filter, Find, and Rank), *approach* (AR and Manual), and *parameters* (single or multiple parameters), where parameters are the product's characteristics. Single is using one characteristic in each task such as sodium, or sugar. Multiple is using a combination of objects' characteristics, such as low sodium and high sugar and low price. The order of the tasks was fixed, but the order of the *approach* and the *parameters* was randomized. The visual representations of this study were based on designs determined from a pilot study. Figs. 2, 3, and 9 depict the visualization approaches employed in our study.

Fig. 7. Situated Information on a product package.

The participants were asked to finish 12 individual tasks. We recorded completion time and errors for each task. Time data were recorded on the tablet, while participants were required to record their answers on a provided paper sheet. In the AR approach the task completion time was recorded automatically from the task start, until the participants clicked on the end button. For the manual task, the participants were asked to click on the handheld device to start the manual task's time recording and click again upon completion. All the tasks results were transcribed to a computer spreadsheet.

After each main task (find, filter, and rank), products on the manual shelf were replaced by new products to avoid any learning effects. The products on the AR shelf were not changed during the different AR conditions as the situated analytics system performs the calculation avoiding learning effects. Moreover, participants were asked not to view or hold any product on the AR shelf.

5.3. Procedure

At the start of the study the participants were asked to complete a consent form, and perform several training tasks before starting the experiment. The training session was performed on a separate practice shelf with four products, to minimize any learning effects. At the start of the each task, we gave the user the required task on a paper sheet. This paper contained the required tasks and assigned the product to be used in the task and query parameters. The task requirements were randomly chosen. Participants did not have a time limit for AR or manual tasks, but were asked to finish the tasks as quickly and accurately as possible.

In the AR approach, the participants were asked to face the AR shelf. They were not allowed to hold and check any information on the product's package manually. They used the AR interaction to select and deselect the product (using camera ray tracing), and used the analytical input panel to assign the query parameter they have been given in the task's requirement paper.

In the Manual approach, the participants were asked to face the Manual shelf. They were asked to use the price tags on the shelf, nutrition information, and the labels on the product package to complete the task. Participants were provided with a pen, paper and writing surface to help them in the query applications. They were allowed to hold and view the product on the shelf.

In the Filter task, the participants were asked to choose all the products on the shelf and filter them based on the parameters given in the task's sheet. For example, one task was to choose all the nut free and locally made products. For the AR approach, the

[3] https://www.qualcomm.com/products/vuforia.
[4] https://unity3d.com/.

Fig. 8. Testbed shopping environment.

participants used the input panel in the AR application to assign the filtering parameters. Then, they recorded the numbers of the product that has been highlighted with a green frame, and to ignore the products with a gray shading and red "X". For the Manual approach, the participants used the provided information on the packages and the tags to answer the filter query. Fig. 2 shows the Filter task's AR information and the analytical interaction.

In the Find task, participants were asked to choose one product from the eight products on the shelf, based on the given criteria on the task sheet. For example, one task was to find the product with the lowest calorie budget, or find the product with the highest protein and lowest sodium content. For the AR condition a green frame highlighted the target product, and all the other products were used as navigation guidance to the target (see Fig. 3). They were overlaid by a semi-transparent layer, and green arrows pointed in the direction of the answer. The participants used the input panel to assign the query criteria. For the Manual approach, the participants used the provide information on the packages and the shelf to find the target answer. They were provided with a pen, paper and assisting tables to help them through the query calculation.

In the Rank task the participants were given four products from the shelf, then asked to rank them based on the criteria given on the task sheet. For example, one task was to select products 2, 3, 5, and 7 and rank them based on the sodium contents, or based on the sugar and price. In the AR approach, participants were asked to select the product first using ray tracing. The ray tracing selection can be achieved by pointing the camera towards the product box, then clicking the select button. Participants could also deselect the product in the same way. After the selection process, the participants used the input panel to assign the ranking parameters. The resulting visual representation of the AR ranking is a ranking value registered on the product's packages (see Fig. 9). The participants were asked to write down the ranking value on a given answer sheet. For the Manual approach, participants were asked to use the provided information on the product's packages and the tags on the shelf to complete the task.

6. Experimental results

The study was performed by 33 participants (24 males and 9 females), with one of the participants having been self-excluded due to a self-reported bias. Their age ranged from 20 years to 66 years, and the mean age was 32.2 years (SD 10.4) participants (three participants did not report their age). Six of the participants reported having AR experience.

6.1. Completion time

We ran the studies completion time results through factorial and one-way repeated measures ANOVA. For all tests unless noted, the Mauchly's test indicated that the assumption of sphericity had not

Fig. 9. AR Screenshot of the Rank Task.

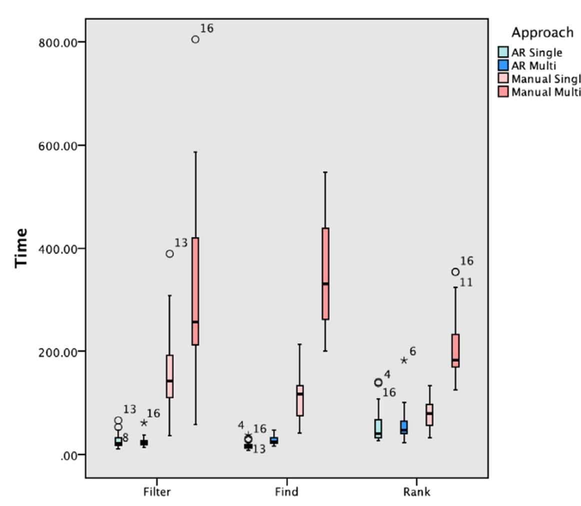

Fig. 10. Tasks' time mean values.

been violated, but when it was violated, the Greenhouse–Geisser corrected tests were reported. For the three tasks: Filter, Find, and Rank there was a statically significant effect of the AR condition faster than the Manual: Filter task $F(1.32, 40.93) = 78.49$, $p < 0.001$; Find task $F(1.33, 41.14) = 339.53$, $p < 0.001$; and Rank task $F(2.06, 63.94) = 150.57$, $p < 0.001$ (see Fig. 10).

We performed a factorial repeated measures ANOVA analysis for each of the three tasks. This analysis has been used to observe the effect of the number of parameters (Single or Multi) on time. There was a significant difference in all tasks: Filter task $F(1, 31) = 26.98$, $p < 0.001$; Find task $F(1, 31) = 228.256$, $p < 0.001$; and the Rank task $F(1, 31) = 103.60$, $p < 0.00$. Employing a Bonferroni post hoc analysis on the results of the three tasks, there was a significant effect between Manual Single and Manual Multi for all of three post hoc analysis. There was no significant effect between AR Single and AR Multi for all of three post hoc analysis.

Finally, we run the data through a one-way ANOVA with AR experience as an independent variable. The results showed that, there is no significant value between the participants with AR experience and the participant without AR experience, for all three tasks.

6.2. Task accuracy

In the Filter task, for the one-way repeated measures ANOVA for the number of incorrect answers and the number of omission targets. The mean number of incorrect selected targets for each condition is as follows: AR-single 0.00 (SD 0.00), AR Multi 0.00 (SD 0.00), Manual Single 0.563 (SD 1.014), and Manual Multi 0.188 (SD 0.397). There were no recorded incorrect errors for both AR conditions. The results of the analysis is ANOVA $F(3, 93) = 8.29$, $p < 0.001$. Employing a LSD post hoc analysis, all pairs were significantly different ($p < 0.05$), with the exception of the two AR conditions. The number of incorrect selections can be ranked as the two AR conditions have the least number of errors, the Manual Multi have the next least incorrect selections, and the Manual Single having the most.

The mean number of omission targets for each condition is as follows: AR-single 0.00 (SD 0.00), AR Multi 0.00 (SD 0.00), Manual Single 0.50 (SD 0.916), and Manual Multi 0.031 (SD 0.177). There were no recorded omission for both AR conditions, with $F(3, 93) = 9.66$, $p < 0.001$. Employing a LSD post hoc analysis, there was a significant difference between AR single and Manual Single with $p = 0.02$, where it shows that there was no significant difference between AR Multi and Single Multi. Employing pairwise t-Test between Manual incorrect and omission, it shows that there was a significant difference with $p = 0.005$,

In the Find task we processed the data with a Pearson's Chi-Square Test to compare between AR-Single verses Manual Single, and AR Multi verses Manual Multi. The results shows no significant value between AR Single verses Manual Single, with $p = 0.28$ and *expected count* $= 4.5$. However, the results show a significant difference between the AR Multi and Manual Multi, with $p < 0.001$ and *expected count* $= 7.0$.

In the Rank task we have continuous and discrete (discontinuous) numerical data. By inspection it appears that there is a significant difference in accuracy of AR Multi versus Manual Multi. Non-parametric tests do not rely on assumptions that the data is drawn from a normal distribution. Thus we perform a two independent sample non-parametric test. A two sample Kolmogorov–Smirnov test (for discrete data) analysis showed a significant effect for the conditions AR Multi versus Manual Multi, $p = 0.01$, and the AR Multi condition had significant less errors. The same statistical analysis was performed for accuracy of AR Single versus Manual Single, but we did not find significant effect, $p = 0.42$.

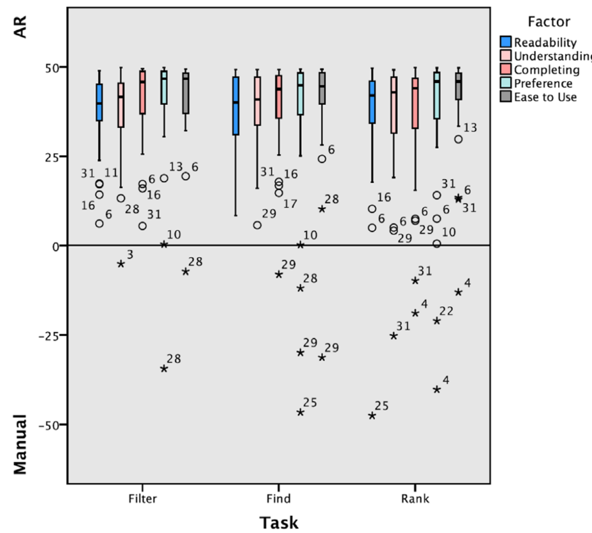

Fig. 11. Qualitative results for Filter, Find, and Rank tasks.

6.3. User preferences

During the user study, we asked each participant to complete a questionnaire. The participants marked a position on a horizontal line to evaluate each task (very poor/hard to very good/easy), and this position was measured and scaled to a number for -50.0 to 50.0. For each task they evaluated the readability, understanding, and completing factors for the AR tasks. They evaluated the preference and the ease to use factors between AR and Manual. We ran these qualitative data through a pairwise t-Test. The results show a significant preference value for the AR approach than the Manual approach with $p < 0.001$ in all the preference factors (readability, understanding, completing, preference, and ease to use). The AR approach was preferred than the Manual approach, 86.4% for readability, 87% for understanding, and 88.3% for completing, 87.4% preference factor, and 90.9% for the ease of use. Fig. 11 shows the qualitative factors for the three tasks, where -50 is the Manual approach and $+50$ is the AR approach.

The user comments indicated that they liked to use our approach for the shopping context. Some of their comments showed that were excited to use our approach in their daily life, such as: “Selecting lower GI items, selecting school snacks, buying for friends coming to dinner with dietary constraints comparing some of these products with too many options to look at manually, i.e. cake mixes, meal bases, bread!!!” and “I would be also interested in expired date and manufactured date”. Moreover, some of the participants suggested to use our approach in other domains that also to enhance the information understanding, such as: “We can use this technology in our chemistry lab, because we have more chemicals and this technology will facilitate the ability to find the chemicals”. However, a number of participants highlighted that they prefer to use their mobile phone instead of the tablet.

7. Discussion

The qualitative and quantitative experimental results show that there is a significant improvement in the completion time and number of errors, when using the AR approach. The results showed a superior user preference in using the AR approach than manual approach. The AR approach provided the users with an efficient tool for performing for complex query calculations. Moreover, the results showed that there were no significant difference between the multiple attributes and single attributes in the AR approach, which reflect that AR approach is not affected by

Fig. 12. Situated visualization displayed on Head Worn Display Epson BT200.

the query complexity. However, the results showed that there is a significant change between multiple and single attributes in the manual approach. The completion time results showed that there was no significant difference between the participants with and without AR experience, which reflects the intuitiveness of the visualization and the interaction techniques.

The results showed that the time to complete a task does not affect the resulting accuracy. When the participants performed the task manually (without AR), they still made more errors than when they used AR. In the Filter tasks the results showed that the number of incorrect error in the manual approach in both Single and Multi attributes were more than the number of omissions. In the real scenario the incorrect errors are more harmful than the omission errors, as the incorrect information means that the user read the information and did not understand it correctly. For example if someone is selecting products that are nut-free, purchasing a product containing nuts due to misunderstanding the packaging is far worse than missing the purchase of a particular nut-free product. However in the Find and Rank task, the results showed that there was no significant difference in accuracy with the Single parameter condition between AR and Manual, but there was a significant improvement using the AR approach over the Manual approach in the Multi parameter condition. This effect reflects the benefits of using situated analytics for complex equations applied in a multiple parameter search. Even though the participants took more time with the Manual Multi condition for both the Find and Rank task, they were unable to determine the correct solution as often as with the AR condition.

8. Conclusions and future work

Situated analytics is a promising solution for enhancing the understanding of information. This potential is increased by improvements in display technologies, including Augmented Reality and wearable devices. In this paper we present *Situated Analytics* (SA), a new interactive in situ decision making technique that combines *Visual Analytics* (VA) with *Augmented Reality* (AR). This combination supports immersive analytical reasoning in the physical space. SA is more than just combining VA with AR. Our new technique changes the paradigm of VA's mantra: Analyze first, Show the Important, Zoom, filter and analyze further, Details on demand. We define a new situated analytics mantra: Details first, Analysis, then Context-on-demand.

We present a set of interactive visual representations for results from multi-dimensional analytical queries. These tools can be used for handheld and HMD devices. The SA approach applies interactive AR information presentations to represent the results of multi-dimensional data analysis. We designed a number of SA approaches for the analysis, visual representations and interactions. We implemented a subset of these approaches into a handheld system, and we validated our concepts with a user evaluation based on a supermarket-shopping context. Moreover, we have upgraded the tested handheld approaches to be employed on HMDs (see Fig. 12).

The conducted study has shown that using our SA technique was faster, less error prone and preferred by the participants over traditional manual methods. In this study we evaluated only the visual representation and interaction portions of our SA approach; however, the whole system still needs to be evaluated in a real life context (i.e. replacing the simulated supermarket with an actual supermarket). This richer environment will provide more challenges for our situated analytic technique and the supporting AR technologies. The techniques described and studied provide an initial insight into how abstract data and relationships such as ranking can be displayed to the user with AR and interactions performed through SA.

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