Situated Analytics

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Abstract—We consider the question of how Augmented Reality can be used for applications that require interactive analytical reasoning embedded in the physical environment. We present novel interaction and visualization techniques for supporting such reasoning, which we call Situated Analytics. Our approach provides situated and abstract information representation with real-time analytical interaction. Three methods of interaction, filtering, finding, and ranking are explored with a diminished reality presentation method employed to highlight analytical results. We conducted a user study to evaluate user performance with three shopping analytics tasks, comparing the Situated Analytics prototype to manual analysis. The results showed that users preferred the Situated Analytics prototype, compared to manual method, and were performed more quickly and accurately.

I. INTRODUCTION

In this paper we present techniques that combine Visual Analytics (VA) and Augmented Reality (AR) to provide real-time situational visualization of multi-dimensional data. Figure 1 shows an example scenario of a user interacting with multi-dimensional data with AR. To demonstrate the potential of this synergy, we have developed and evaluated an application that exemplifies how interactive visual representations can support users in the manipulation of complex data mapped to physical artefacts with AR.

This paper draws on two research areas: Visual Analytics and Augmented Reality. VA was introduced as “the science of analytical reasoning facilitated by interactive visual interfaces.” [22] Building on scientific and information visualization, VA is a multidisciplinary field covering analytical reasoning techniques; visual representations and interaction techniques; data representations and transformations; and techniques to support production, presentation, and dissemination of analytical results [22]. The second research area, AR, enriches the physical world view with in situ registered computer-generated information and can provide the user with contextual information in real-time [28], [1]. In this paper we consider the question of how to support VA’s analytical reasoning by embedding the visual representations and interaction of the resulting data in the physical environment using AR. We call this new area at the intersection of VA and AR situated analytics [4].

The necessity to discovery approaches to comprehend and analyze complex and frequently large data sets is a continuing research challenge. In numerous applications the results of VA are tied to a physical location or specific entity, such as the presentation of geological information for mining in the field, medical data for emergency services, and selection of products given a list of requirements. AR brings a novel dimension to the information presentation by permitting the visualizations to be heightened with physical objects that provide contextual information and form part of the reasoning used during interactions. We believe situated analytics is a method that can be established to fulfill the need of enhanced approachability and speed when reasoning with location-based multi-dimensional data.

To achieve this goal, there are a number of challenges to be overcome at the intersection of VA and AR research, in particular the area of visual representation, interaction and applicability. Traditional data visualizations do not effectively link the visualizations to objects or locations in the physical world [20]. How should AR represent different kinds of abstract data (categorical, rank, numeric, temporal, spatial etc.) that are associated with physical objects [26]? How should abstract relationships, such as connectivity or ranking, between physical objects be shown to the user? This form of technology should not interfere with a user’s everyday activities but instead enhance them with additional information [23].

This paper builds on White and Feiner’s work in situated visualization [26]. Situated visualizations allow the user to gain meaning through the fusion of the visualization and its proximity to the physical environment. While the data in White and Feiner’s SiteLens system is multi-dimensional, their visualizations do not support real time analytics and interactive manipulations of the analytics. To our knowledge this is the first investigation into the application of AR technology to visual analytics. Our main contributions are as follows:

- We present situated analytics a novel method of interactive exploration for multidimensional data that is designed for use in AR enhanced applications.
- We present a set of visual representations for displaying results from multi-dimensional data queries that are designed for use in AR enhanced situated analytics applications; in particular these techniques are filter, find, and rank of co-located physical objects.
- We present the results of a user-evaluation that focused on the visual representations and interactions aspects of the situated analytics system. The context of the evaluation was placed in a supermarket shopping application in which users were asked to select, rank and filter grocery products based on their price, ingredients and nutritional benefits.

One critical issue in situated analytics is the mode for interactive data exploration. Traditional information visualization supports open-ended exploration based on Shneiderman’s information mantra: overview first, zoom and filter, then details on demand [19]. Keim [12] modified this for VA: Analyze first, Show the important, Zoom, filter and analyze further,
comparatively little research into data visualization employing present visualization and visual analytics. There has been A. AR Visualization and V A is the emphasis on open-ended interactive exploration approach are the data type and the display space [19]. The that the two main attributes that can affect any visualization patterns in more abstract data [19]. Shneiderman explained purposes [18], while physical (including spatial) data for simulation and observation into two fields. The paper finishes with set of concluding remarks. The user study and its results are then described. situated analytics approaches, the interaction and visual repre-

This focus on particular objects in the environment suggests that for situated analytics the interactive data visualization should almost be the reverse of Schneideman’s or Keim’s mantras. Rather than starting with an overview or the results of a global data analysis, the user should first be provided with details concerning the visible objects. Subsequent interactive analytics is focussed on these objects and the results of queries are displayed in situ. Global and contextual information is only provided on demand. The situated analytics mantra is: Details first, Analysis, then Context-on-demand.

There needs to be a better understand when situated analytics is useful and the trade-offs between it and more traditional. We are also interested in exploring real world tasks to support users in decision making through the use of multi-dimensional data that is presented through AR, making it more easily accessible compared to manual data analysis.

Following the Introduction, Section II discusses the related work of AR, Visualization, and VA. Section III details our situated analytics approaches, the interaction and visual representations. The user study and its results are then described. The paper finishes with set of concluding remarks.

II. RELATED WORK

Data visualization research has been traditionally divided into two fields. Scientific visualization is used to display physical (including spatial) data for simulation and observation purposes [18], while information visualization is used to reveal patterns in more abstract data [19]. Shneiderman explained that the two main attributes that can affect any visualization approach are the data type and the display space [19]. The main difference between traditional information visualization and VA is the emphasis on open-ended interactive exploration of data facilitated with sophisticated analytics.

A. AR Visualization

Traditional displays are the most common method to present visualization and visual analytics. There has been comparatively little research into data visualization employing AR, and to our knowledge AR has not been applied to visual analytics. There are a number of challenges for AR due to current technologies, and some of the main challenges are tracking in unprepared environments, registering virtual information onto physical objects in these unprepared environments, and the limitations of current display technologies [14]. Denis Kalkofen et al. [10] classified the visualization techniques in AR into three main types: data integration, scene manipulation and context driven. Data integration techniques [6] are used to enhance the appearance (registration, rendering, and occlusion) of the virtual objects in the physical world. Scene manipulation techniques [11] are used to manipulate the real scene to add new information. Context driven techniques [26] are used to alter the visualization appearance based on the scene context. The challenge of context visualization in AR increases with the increase of the amount of information presented to the user. In the previous work researchers tried to solve this challenge by three main methods: complexity reduction, layout optimization, and interaction techniques.

Data filtering is one of the common complexity reduction approaches used for AR visualization. Researchers have proposed a filters approach to reduce the amount of presented on the AR display. These filters are based on location [16], user profiles [7], or tasks [8]. However, there are other approaches that combine multiple filters to reduce the information, Jose Ma Luna et al. [17] used location and point of interest as a filter for data reduction.

Layout optimization is another approach used to solve the large information challenge in AR. Azuma and Furmanski [2] proposed a view management approach for text annotation arrangement. Bell et al. [3] presents a view management approach for text and images. The main advantage of the Bell et al. approach is that the annotations size change with respect to the user’s view. This approach uses filtering methods to reduce the data presented based on the user’s view. The Bell et al. investigation reflects a potential solution for large information visualization by combining data filtering and layout optimization tools. Tatge and et al. [21] proposed a technique for view management in AR to solve cluttering by mapping the annotations into 3D space instead of 2D space.

The Touring Machine [5] was one of the earlier approaches that provide interactive AR visualization tool. The Touring Machine employs a head worn display attached to a wearable computer to highlight key points of interests and supports
interactions on a hand held tablet computer to navigate between a numbers of hyperlinks describing information about the Columbia University’s campus. This approach presents a solution for tree-structured data, but cannot be applied to multidimensional data, because the data visualization’s relationships are static (hyperlinks and locations). Walsh and Thomas [25] developed an outdoor wearable AR visualization system for environmental corrosion data. The goal of their system was to reduce the effort of manual inspections required for large structures, such as bridges. The wireless environmental sensors have been designed to automate this process, and the AR visualizations are designed to ease the access to the sensor data. The visualizations are of live and historic sensor data presented in situ with the placement of the wireless sensor.

B. AR Visualization of Complex Data

White et al. [27] presented one of the earlier approaches to visualize multidimensional information in AR. Their approach allows users to inspect a static database; queries were performed by computer vision techniques to recognize physical objects. Their approach employed tangible interactions to explore the data and compare solutions. However, working with abstract information requires a more generalized visual representation than that presented in White’s approach. An approach for presenting time-oriented data in AR has been proposed by Zollmann et al. [30]. Their approach represents the information based on predefined relations, and allows users to view and expand details on demand.

The need of abstract multidimensional information visualization is one of the main challenges facing AR browsers [15], [13], as the existing visualization approaches led to the masking of large quantities of data and their relationships. The masking problem with AR browser approaches make them not compatible for decision making, such as searching, comparing, and clustering. Eduardo et al. [24] proposed interactive visualization approaches for AR monitoring, but these are for application specific purposes.

Information visualization in AR may be employed in different domains. The shopping context is one such domain that has received notable interest\(^1\). Zhu et al. proposed an in store e-commerce context-based system [29]. They employed AR on a hand held tablet PC to improve the user’s shopping experience. Although this approach works with multivariate data, their approach defines dependencies between the data based on a predefined clustering. This approach limits the user’s query options. Kahl et al. [9] employed RFID and touch screens to guide users in the shopping based on their predetermined shopping lists, and the supermarket map.

In summary, the two existing solutions for the large multidimensional for AR are as follows: 1) filter the amount of the presented data and 2) by interactive exploration tools. However, these filtering techniques lead to masking of large quantities of data, which made them not compatible for decision-making purposes. Moreover, the existing visualization interaction tools for AR employ static data relationship to navigate through them, for instance 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, however in our approaches we use applied the analytics to the user interaction, which allow users to view the information from their own perspective.

III. SITUATED ANALYTICS

The central objective of situated analytics is to afford users the ability to visualize the result of complex queries in context with a physical object. In this section we present our new situated analytics approaches, interactive filtering, finding and ranking of objects in the physical world based on multidimensional information about the objects. The approaches are illustrated in the context of tablet AR technology that employs video see-through AR technology to register the information in the physical world. Our results are not limited to video see-through and hand held display technologies; we envision situated analytics to be applicable to other forms of AR such as optical see-through HMD’s. Figure 2 depicts an overview of the interaction and visual representations provided in our situated analytics approach. There are four main UI elements: presentation of abstract information, presentation of situated information, UI controls for analytical interactions, and UI controls for AR interactions.

![Fig. 2: Situated Analytics system interaction and visual representation](image)

A. Interaction

The key difference between AR visualization and situated analytics, is that situated analytics permits a user to continuously analyze, interact, and visualize data in situ. The user can interact with a system to alter the analytics’parameters, which directly reflect in results. We present two interaction approaches for the situated analytics: Analytical interaction and AR interaction.

Analytical interaction allows the user to control the analytics. Through these interactions users can modify the type and form of analysis applied to the data registered to the physical objects. A naive approach would be to present the formulas of the analysis to the user and ask them to modify...
such elements as constants and variables. Our approach is to bind the analytical interaction 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 allow the user to construct queries that encode a series of binary options. When only one option from several can be made, as in the case of orthogonal relationships, radio buttons are employed. Sliders are employed to allow users to specify a ratio between two extremes. The analysis for situated analytics is application specific; therefore, each binding of analytical interactions will be unique to each application.

The AR interaction allows users to interact with the physical objects in context of the queries, such as select and deselect an object, which allows users to filter the information and explore data on demand (DoD). Figure 2 depicts a user selecting a physical object, as the user highlights the physical object and presses the “+” button. 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 pointing the camera at the object, and pressing the select/deselect buttons. These buttons are placed in a position to be comfortable to use in a reachable area under their thumbs.

B. Information Visual Representation

Our information visual representation approaches are divided into two main types: situated information and abstract information. The situated information is registered on the physical objects. The location and appearance of this information dynamically changes based on the tracking information, and the representation is altered based on the analytical interaction and AR analytical interactions. The abstract information is used to visualize the overall context. For both situated and abstract information, we use the saliency cues of size, color, and orientation to encode information.

1) Situated Information: Situated information is used to present the results of analysis as AR registered information attached to the physical objects. These visual representations present results based on users queries. We investigated how to represent the results from the following three different kinds of queries: filtering, finding, and ranking. Our goal is to apply visualizations that are informative, easy to understand and intuitive.

The visual representation for filtering is the result of a user’s filter query. We developed a visual representation that allows physical objects to be displayed without occlusion or partially masked with a transparent overlay - we call this method diminished reality. Figure 1 (a) shows the diminished reality method with 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”. This technique can be modified to employ for situated color-coded clustering, by modifying the visualization input to be integer value rather than a Boolean, and changes to the visualization’s size and color are now based on the input integer value.

Visual representation for finding an optimal result based on searching query on at set of physical objects. The particular weighted function is specified through an analytical interaction. Figure 1 (b) depicts our visual representation for a finding query. The target is highlighted by green frame, and the other objects are hidden with a semi-transparent black object overlaid visual green navigation arrows to the target. We leverage the AR annotations of the hidden objects to guide the user to the location of the correct result. We assume 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.

The visual representation for ranking is used to inform the user of a sorted subset of physical objects. 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 to be analyzed. In this way the user may view the effect of adding or deleting a particular object has on the ranking. The Figure 1 (c) depicts one of a number of visualization options we have developed. Our ranking visualization approach employs the saliency cues of size and color to reflect the sorting value. Equation 1 shows the algorithm which changes the size of cue with respect to the ranking value of the object (Vs). The size value is change within a range between zero to the maximum scale factor (Sy, Sx, Sz). This factor values is a ratio determined from the physical object’s dimensions. The color of the visualization is a mixing value between red and green.

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\text{Size}(x, y, z)_t = ((S_{x_{\text{max}}}/V_{s}), S_{y_{\text{max}}}, (S_{z_{\text{max}}}/V_{s}))
\]

\[
\text{Color}(x, y, z, a)_t = ((V_{c_{i}}/n), 1 - (V_{c_{i}}/n), 0, 1)
\]

2) Abstract Information: The abstract information is used to represent the global context. A problem with situated analytics 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. Figure 2 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 of the analytical interaction and the AR interaction.

IV. User Study

We conducted a user study to validate a portion of the UI design for the situated analytics and to evaluate the usefulness of the presentation of AR information to enhance information understanding. We employed a situated analytics shopping prototype to evaluate our techniques. The focus of this study was on the AR interactions and situated information aspects of the system. In the study we compared the use of the situated analytics prototype against reading information from the products and completing the same task manually. Standard products from a local supermarket were used to complete three tasks where participants were asked to perform: Filter, Find, and Ranking. We measured user preferences, time taken to complete tasks and errors made completing the tasks. We measured errors where the participant select the wrong product,
an incorrect error, and when the participant failed to make a selection of a product was an omission error.

Fig. 3: Testbed shopping environment

A. Equipment

We conducted the experiments in a mock-up shopping environment with two standard sets of bookshelves to serve as shop shelves, one for the AR tasks and the other for the manual tasks (see Figure 3). We chose to use eight products on each shelf so participants could complete the manual analysis quickly, and we believe customers in the supermarket shopping context would not commonly compare more than eight similar products whilst in situ shopping. 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 applications were developed with Vuforia\textsuperscript{2} and Unity\textsuperscript{3}.

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 starts when the users pressed on the task button on the tablet and ends after they pressed the End button.

B. Study Design

The visual representations of this study are based on designs determined from a pilot study. Figures 1 (a), 1 (b), and 4 depict the visualization approaches employed in our study. The experiment was a 3 x 2 x 2 repeated measures design. The independent variables examined were tasks (Filter, Find, and Rank), approach (AR and Manual), and parameters (single or multiple parameters). The order of the three tasks order was fixed, but the combined order of the approach and parameters conditions were randomized. The participants were asked to proceed from one task to another until they finished the 12 individual tasks. The dependent measures were completion time and errors. Participants took part in all conditions of the experiment. Participants recorded their answers on paper sheets. Errors were determined from comparing the answers on the paper to a correct solution, and these results were transcribed to a computer spreadsheet.

The products in the manual shelf were changed after each main task (a total of 24 products), to avoid any learning effects. The products in the AR shelf were not changed during the different AR conditions as the situated analytics system performs the calculation avoiding learning effects. Participants were not allowed to hold the products from the AR shelf, and they were not able to view any of the product information on the packages. In both the AR and Manual conditions, we used the per serving value on the products’ nutrition labels.

C. Procedure

At the start of the experiment the participants asked to sign a consent form and complete a task rehearsal through a practice session. The practice session was performed on a separate practice shelf with only four products for the AR and Manual conditions to avoid the learning effects. At the start of each task, we gave the participants a paper sheet. These sheets described the task and the parameter criteria. The paper assigns which products and parameters they will use in their tasks. These were randomly assigned.

In the AR approach, the participants were asked to face the AR shelf. They used the analytical interaction input panel to assign the parameters, which they have been given on the paper sheet. The participants based their answer on the information provided from the AR information portion of the prototype. They recorded their answer on the paper sheet based on the AR visualization.

In the Manual approach, the participants were asked to face the Manual shelf. They used the nutrition labels, ingredients on the product package labels and the price tags to search for the correct answer. All participants were provided with pen, paper and assisting tables, to help them to calculate the answer. The participants were able to hold and view any side of the products on the shelf.

In the Filter task, the participants were asked to choose all the products on the shelf that matched the attributes given on the sheet. For the AR tasks they used the application on the tablet to determine the correct products. For the Manual tasks they used the ingredient information mentioned on the products packages. An example of the Filter task was to choose all the product that have the following attributes: gluten free, nuts free and locally made. Figure 1 (a) shows the Filter task’s AR information and the analytical interaction. The AR information highlights the answer with green frame and other products are indicated to be ignored by a grey shading and a large red “X”. The participants were asked to tick all the choices as results on a paper sheet.

\textsuperscript{2}https://www.qualcomm.com/products/vuforia
\textsuperscript{3}https://unity3d.com/
In the Find task, participants were asked to choose products that match the given criteria on the paper sheet. An example of the Find task is to choose a single product with the following attributes: lowest salt, lowest saturated fat, and highest protein. For the Find task (see Figure 1 (b)), the answer was highlighted with green frame and the other products were blocked and overlaid with navigation arrow to guide users to the answer more quickly. The analytical interaction panel contains toggle buttons that the participants used to assign low/high values for the parameter. They assign the values via the buttons based on the provided parameters on the paper sheet. To finish the task, the participant asked to find the correct product write down its number on the paper sheet. In the case of the Manual approach, the correct product must be determined through reading the product information on the packages.

The Rank task had the participants select four products with a given set of attributes, and then rank the four chosen products. The particular products and the ranking attributes were randomly generated, and this information was given to the participants on the paper sheet. For the AR approach, the participants used AR information on the tablet. For the Manual tasks, they used the nutrition labels on the product packages and the shelf price tags. Figure 4 depicts the Rank task’s interface. For the Rank task we used numbers to present the ranking value on a green background. The analytical interaction input panel contained toggle buttons to assign the required products. To finish the tasks, the participants needed to rank the products and fill their correct order on the paper sheet.

V. EXPERIMENTAL RESULTS

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

A. Completion Time

For the completion time of Filter, Find, and Rank tasks, we run the study 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 been violated, but when it was violated, the GreenhouseGeisser corrected tests was reported. For all three tasks 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 Figure 5).

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 $F(1,31) = 103.60, p < 0.001$. 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.

B. 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 ranking 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 versus Manual...
Single, and AR Multi versus Manual Multi. The results show no significant value between AR Single versus Manual Single, with \( p = 0.28 \) and expected\( \text{count} = 4.5 \). However, the results show a significant difference between the AR Multi and Manual Multi, with \( p < 0.001 \) and expected\( \text{count} = 7.0 \).

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 Mult 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, \( p = 0.42 \).

C. 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 -5.0 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. Figure 6 shows the qualitative factors for the three tasks, where -50 is the Manual approach and +50 is the AR approach.

![Fig. 6: Qualitative results for Filter, Find, and Rank tasks](image)

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.

VI. DISCUSSION

All the experimental results show that there is a significant improvement of AR approach over Manual approach in both completion time and number of errors. The AR condition results show a superior user preference than the Manual condition. The superior time to completion results of the AR interaction provided users with the ability to quickly perform detailed analysis of complex multi-dimensional data. Moreover, the results show that there is an improvement between the single and multiple parameter conditions in the manual task, and an insignificant difference in AR. This reflects that the completion time was effected by the complexity of the task for the manual condition, and the completion time was not effected in the AR condition. The completion time results show that there is no significant difference between the participants with and without AR experience, which reflect the intuitiveness of the visualization and the interaction techniques.

The results show the time to complete a task does not affect the resulting accuracy. When the participants perform the task manually (without AR), more errors occurred with increased task completion time. In the Filter task with the Manual approach, the results show that the number of incorrect errors was greater than the number of omission errors with both Single and Multi parameters. This indicates that the Manual process impedes the participant’s understanding of the information more often than causing the participant not to be able to find the information required. In a real world scenario, the misunderstanding of the information concerning a product may be more harmful than not finding the product. For example if someone is selecting products that are nut-free, purchasing a product containing nuts because of not understanding the packaging is far worse than missing the purchase of a particular nut-free product. However in the Find and Rank task, the results shows that there is no significant 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 the 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.
VII. CONCLUSIONS AND FUTURE WORK

In this paper we present Situated Analytics, a new interactive in situ decision making technique that combines VA with AR. Situated analytics 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. The situated analytic approach applies interactive AR information presentations to represent the results of multi-dimensional data analysis. We designed a number of situated analytic 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.

This study has shown that using our situated analytic technique was faster, less error prone and preferred by the participants over traditional manual methods. Our new approach reflects a potential for enhancing the information understanding. In this study we evaluated only the visual representation and interaction portions of our situated analytical 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 situated analytic.

REFERENCES


