Intelligent Wearables

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***Abstract*— Wearable devices are ever more becoming an asset in our everyday lives. This shift to ubiquitous computing has also led to the development of systems that make these wearable devices behave intelligently according to a user's need, when deployed in various scenarios. The system discussed here, is envisaged to be deployed in a tourism environment as a personalized suggestion generation that relays information back to the user through an Augmented Reality framework. The implementation explored the use of various techniques in literature, and a series of tests were performed in order to evaluate the system's personalization capabilities and its perceived efficiency. The Precision rate obtained was 81%, while Recall and F-Measure, stood at 60% and 65% respectively. Future work on this study opens the door to the implementation of such systems that allow for the development of intelligent wearable devices that can be both useful in increasing accessibility or simply entertainment.**

Keywords- Profiling; Ontology; Augmented Reality; Intelligent recommendations; Implicit data gathering; Explicit data gathering; rule-based approach; Synsets; Precision; Recall; F-measure; tf-idf

I. INTRODUCTION

Artificial Intelligence (AI) "is the science and engineering of making intelligent machines, especially intelligent computer programs" [1]. Therefore, it is fair to conclude that the design and implementation Intelligent Wearable devices, devices that can adapt to the user's needs and behavior, is at the very core the field of Artificial Intelligence. We are now witnessing a shift to ubiquitous computing that has made it possible to have intelligent systems operate as effectively on mobile devices, and deployed in various scenarios without compromising on performance while incorporating new technologies such as Augmented Reality. One scenario where such systems can be deployed effectively is in the tourism domain in the form of Landmark Recommendation engines for tourists.

The tourism industry is an ever growing industry which caters for people of all ages, who come from various areas of life and more importantly, whose travel interests tend to differ. One such major difference would be that, while members of the older generations tend to prefer going on organized tours where a person is giving out information about any landmarks in the surroundings, members of the younger generation would rather roam freely about the city discovering what there is to be discovered by themselves. In addition, people tend to look out for different attractions when they are abroad which vary from tourist to tourist depending on the person's interests.

The development of wearable devices that behave intelligently, and that can be deployed in such scenarios would not only be interesting from the point of view of research, but also a step into what will soon be the norm for most devices we have around us [6][8]. The aim of this research is to make such wearables act intelligently by having the device generate recommendations tailor made for the individual. Acting intelligently also involves the presentation of relevant information to the user at the time when this is actually required. Such tasks involve the implementation of user-profiling mechanisms in order to be able to understand the traits of the user and in turn generate recommendations that are as accurate as possible. Deployed in the aforementioned domain, such devices would ensure that any tourist visiting a foreign city gets the opportunity to explore the city better, without hindering his visit with the cumbersome tasks of having to carry with him devices which are not very user friendly. Therefore, finding the right techniques with which to gather information, present it in structured formats, and, more importantly, infer user traits from the data at hand, is pivotal in the creation of such systems.

Section 2 gives an insight into the Aims and Objectives that this paper aims to achieve. While Section 3 provides an overview of related work, Sections 4 and 5 provide a description of the design and the implementation of the system respectively. Section 6 presents the results from the evaluation carried out and Section 7 provides an insight into future work. Finally, Section 8 provides a conclusion for the work carried out.

II. AIMS AND OBJECTIVES

The aim of this research is to investigate the best practices and techniques of building an accurate user profile from social media, to provide accurate recommendations that will sustain the operations of the intelligent wearable device. In order to achieve this, the following objectives were identified:

1. Building and representing a user profile from any source of data relevant to the cause and ensuring that mechanisms employed keep a representative profile which is up-to-date. Returning the recommendations of landmarks which may be interesting to a user, and extracting information from web sources to be returned to the system user.

2. Through the use of the mobile application notify the user whenever he is close to the landmark and provide on screen tailored information through an augmented reality framework.

The extent to which each of these objectives was satisfied by this study is as follows:

- The first objective was ultimately achieved through the personalization component. Through the tests performed accuracy results for this component were recorded at 0.81 precision average, 0.6 recall average and 0.65 f-measure average.

- The second objective was achieved through the information visualization component.

III. Related Work

Research carried out focused primarily on personalization systems, mainly on how to construct efficient and effective user profiles. The ultimate goal of user-adaptive systems is to provide users with what they need without them asking for it explicitly. The idea of Automatic Personalization is central to such systems [2]. The ability of a personalization system to tailor content and recommend items implies that it must be able to infer what a user requires on previous and current interactions with the user. Tourist recommendation systems are all the more becoming an integral contributor to the concept of e-tourism services. Most recommendation systems tend to focus on helping the user select the travel destination while others tend to focus only on some aspects of the holiday. For example, Entrée [3] uses domain knowledge about restaurants, foods and cuisines to recommend restaurants to users while MastroCARonte provides personalized tourist information (hotels,restaurants, places to see or visit) on-board vehicles. In 2012, F.-M. Hsu et al. [9], came up with an intelligent recommendation system for tourist attractions [8]. Similarly, one can find CAPA, a personalised restaurant recommender that rather than being browser based, works on a mobile device. Systems such as the GUIDE system [4] and WebGuide [5] give the user a personalised experience when visiting cities such as Lancaster, Heidelberg and Vienna, through the way in which information is fed back to him. Other systems such as IMA provide services in a wide geographical area. CRUMPET proposes touristic sights' and uses advertisements to promote all kinds of services that may be helpful to any tourist [9].

IV. Design

For development purposes, the system was drawn up into a number of components and subcomponents that communicate with each other to achieve the final goal of an application that works on a wearable device. Figure 1, shows an abstract representation of the proposed system and its main components. For the scope of this study, Android mobile applications, especially in view of the ease with which to create such applications, are ideal to implement the application component while Apache servers provide an ideal platform on which to host server side scripts that help the application with its tasks. Having the system planned out in this manner return provides many advantages mainly for the fact that by delegating the heaviest tasks to the server, the application on the mobile device can focus its resources on other areas. Also, any future updates to the system would require the alteration of some scripts on the server rather than having to modify the application's structure.

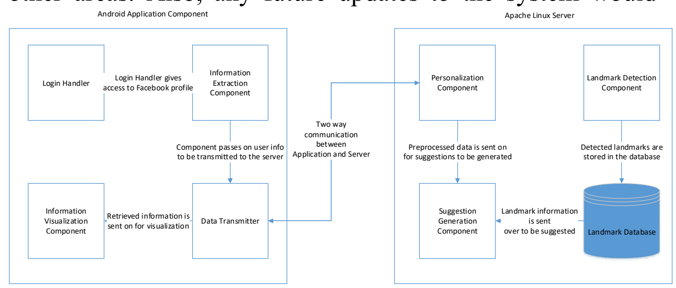

Figure 1. A diagram of the proposed system.

The first major component of the system is the Android Application component, which is first and foremost responsible for handling login operations that will in turn ask for information from a about the user and then triggering and handling the results obtained by the operations of the other sub components. For this function, social media was considered, mainly due to the fact that social media accounts tend to have an enormous amount of wealth of information about the user. The second component is an Apache Linux server component that through communication with the application that will be deployed on a wearable device, reduces much of the computational burden from the application side by handling the more cumbersome components of the system mainly, the personalization component. This component is also responsible for handling the presentation of the final system results.

The application component, as shown in the diagram below has a number of sub-components each responsible for handling specific tasks that give the application, and the whole system, its functionality. These components include a login handler component, an Information Extraction component, a JavaScript Object Notation (JSON) transmitter and an Information Visualization Component. The Login Handler component, as the name suggests is responsible for handling social media login requests by the user and works in tandem with the Information Extraction component to obtain the required information from the social media profile. Given that the application must in some form or another send and also receive data from the second component, the JSON transmitter component is critical for what the system is trying to achieve. This component provides the means of communication between the application and the server through the device's network services. The final module in the application component is the Information Visualization component. This component is responsible for displaying graphically the information that the application component receives from the server. Taking into consideration the various types of wearable devices, the most suitable device for such this proposed system is a head-mounting device. However, this is not its only use, as this component is also responsible for handling location tracking for the device and also for performing arithmetical operations to know when the device is actually required to display the retrieved information.

The server component has a number of sub-components as well, which components are responsible for handling specific tasks in relation to the personalization capabilities of the system. These components include a personalization module that prepares the received data for the generation of recommendations, and a Suggestion Generation module. The latter is tasked with building the user profile from the information retrieved from the application, and generating the suggestions based on the user profile built earlier. These suggestions are then transmitted back to application. In addition to these two modules, the server component also consists of a database that contains the information about landmarks in the city being visited, from which the suggestions are to be drawn.

V. Implementation

A. Information Gathering

The first task of the application is to gather information about the user. As previously discussed, this information is to be extracted from social media profiles and for this reason Facebook was chosen as the platform from which to gather the required information. The choice to go for this particular social media platform stems from the fact that as of 2016 it is estimated that Facebook has 1.59 billion users and therefore it is fair to say that it is one of the most popular platforms in the area. More importantly, Facebook profiles tend to be much more indicative about their users given the type of information people share. Facebook's Graph API is therefore used to obtain the desired information which information varies from personal information, such as demographics, to particular likes such as interests, artistic groups, and so on. The information is supplemented with information from the user's social media feed in order to ground it within a temporal context. The idea is to make the harvesting of the information as implicit as possible requiring only a minimal amount of explicit data input from the user. The user's 100 most recent likes and 25 most recent posts to his or her social media profile are taken into consideration and are later on analyzed to achieve the personalization objective. This amount of data is ideal since it finds a balance between having just about the right amount of data to be able to perform user profiling without overloading the application with information to be sent to the server, and eventually read back, making the application process too slow. In addition, this amount of information provides an ideal temporal context that makes sure that the information being used to achieve personalization is in fact based on the user's most recent activity which is indicative of his or her present interests.

B. User Personalisation

The first step in user personalization involves preparing the data for analysis. Essentially what this step does is that it receives the data and performs tokenization and stop-word removal. For the purpose of this implementation sentences were tokenized in order to be able to see the data in the form of words which makes it more practical to analyze. Stop-word removal, on the other hand, removes from a list of words very commonly occurring words that more often than not do not have any relevance to the subject of the sentence. Through the application of stop-word removal it is ascertained that the tokens that will be analyzed actually have a certain degree of importance and would actually contribute to the end result to be obtained by the system.

Finally, after applying the aforementioned techniques, the system uses an ontology, in this case WordNet, in order to find the synonyms of all the remaining tokens in the gathered data. At the end of this process, the system is left with two data items that are crucial for the continuation of the profiling process. These are the list of remaining words after applying stop-word removal and a list of words with their synonyms. Upon termination of the first phase, the data next needed to be passed on for further processing.

C. User Profiling

User profiling can only start taking place when the data is properly prepared after completion of the above mentioned steps. However not until a further few steps are carried out, can the actual task of building the user profile be carried out. The first of these steps involves the introduction of tf-idf in order to be able to classify the words in the gathered data according to their importance. What this means is that if a word occurs more times than others then it will have a higher tf-idf value than the other words, which is precisely what is needed in this case. For the purpose of this implementation, the corpus includes all the information retrieved from the user's profile. Through calculation of tf-idf values the system creates a data structure consisting of data-pairs where each pair contains the word and its perceived importance, and how it is able to identify the most commonly occurring words. These words are considered to be the most important words which in turn will be used to base any assumptions for building the user profile. This reasoning stems from the thought that if a person talks or searches about some specific things, then one can deduct that the person is interested in these things. Consequently, these most commonly occurring words are considered to be indicative of the user's interests. For the purpose of this study the 200 most commonly occurring words are taken into consideration. It was felt that such a dataset size can give a sufficiently vast dataset on which to perform the remaining tasks.

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1) Building the user profile

User-profiling adopts a hybrid approach between Weighted Key-word representation and the Semantic representation. It finally employs categorization into specific groups in order to improve uniformity. There are twelve identified categories which are: “photography”, “shopping”, “history”, “military”, “food”, “religion”, “art”, “technology”, “science”, “music”, “sport” and “nature”. These identified categories also correspond to the categories of landmarks as classified by TripAdvisor. For each interest category identified, the synonyms were also identified once again through WordNet as a reference ontology, and the use of Node.js modules.

The profiling process is split up into three phases in order to ensure utmost veracity when the final results are achieved. The first stage involves comparing a set of words, deemed to be the most frequently used words by the user after analysis of the gathered data to the groups that correspond best to the landmark categories. Thus if the list of most commonly occurring words contains some word that is found in the list of identified interests, then that particular interest category is marked as relevant. Although this is one form of classifying the user, it was deemed too trivial and too risky when considering the result accuracy. As a second measure of profiling the word ontology results are introduced by which the system compares the synonyms of the most frequently used words to the stereotype categories. To further complement this, in the final stage of categorization, the system also looks at the synonyms of the landmark types and performs one final check in order to categorize the user into the most representative categories based on his interests. This ensures that if the list of most commonly occurring words does not contain the exact name of an interest field, then more checks are carried out to increase the chances of obtaining a hit. At the end of this cycle the result would be a user profile consisting of the interest fields that are deemed to be of interest to the user.

2) Generating suggestions

The only remaining task to do at this stage for the system is to generate the recommendations. The identified interest fields have a set of allocated landmarks which will, in turn, be recommended to the user by the wearable device. For example, if the user profile has the ‘food’ category ticked, then the system will return to the user a list of all the landmarks that fall under the ‘food’ category in the landmark database.

This database is generated through calls to the Google Places API. These calls in addition to returning the name of the landmark, its geographical location and reviews about the place, also returns a list of categories under which these landmarks can be classified. It is through these returned categories that the landmarks are classified in the landmark database and eventually recommended back to the user. This component makes the system extremely flexible, in the sense that with just a simple update of the landmark database through API calls, the system can be deployed virtually everywhere that is covered by Google Maps. These suggested landmarks are then returned to be visualized on screen.

D. Information Visualization

The final component of the system is the Information Visualization component, which is responsible for visualising the suggestions on the wearable device and which is implemented in its entirety on the application side. In order to achieve a functional Location-based Augmented Reality, which is the approach chosen for this implementation, the undertaking of the following steps was necessary prior to the actual Augmented Reality framework construction:

- Getting the GPS location of the device
- Getting the GPS location of destination point
- Calculation of the theoretical azimuth based on GPS data
- Getting the real azimuth of the device
- Comparing both azimuths based on accuracy to then call an event

1) User Location and Azimuth Angles

Keeping in mind the application’s objective, it is imperative for the application to constantly know the user’s location in order to be able to augment the user’s view with information that is relevant to landmark which is in view. Location details are obtained through the device’s GPS whereby, with the use of listeners, the user’s coordinates are updated periodically. This was implemented by GoogleApiClient requesting location updates at a predefined interval between each request. When the application senses that there is a change in movement, location is updated.

The system must also calculate the user’s azimuth angle since the implementation approach chosen is based on the geodesy theory. Calculation of this angle is necessary for triggering the on-screen visualization of the landmark information, and the process of getting this calculation relies heavily on the use of the device’s sensors.

2) Object Identification

Location data is pivotal to achieve whatever needs to be done in this component since the system adopts a Location-based Augmented Reality approach. What this approach entails is that the device does not know what the landmark actually looks like, but rather where it is. Since the system is being deployed in a scenario where it is required to suggest landmarks to its user, this approach fits the requirement perfectly because a landmark is hardly ever going to move, and should it move, for example if a restaurant relocates, the system can work just as fine with a simple update of the landmark database.

As already mentioned the system keeps track of the user’s location at regular intervals and this data is, in turn, used to augment the screen with the landmark information. Apart from this it also makes sure that whatever data is presented on screen, it is relevant to the landmark actually in view. In order to be able to function, the Visualization Component relies on the landmark data file transmitted by the server. As soon as this is available the component becomes active. It first reads every suggested landmark from the retrieved list, and then creates a data structure of landmark objects where each object contains the landmark name, its location and any relevant reviews. When the application is fully aware of what landmarks exist then visualization can begin.

The aim of the application is to be able to return information on screen whenever a landmark is in view. It does not require to have multiple pieces of information about various landmarks at any one time on screen. This, however, required the implementation of a method that is able to identify the nearest Point Of Interest (POI) which would allow the application to augment the screen with the relevant information pertaining to the landmark which is closer to where the user is at a point in time. It is in this manner that Object Identification was implemented. The application constantly updates its knowledge about the landmarks. At any one time it knows that when a user is at a particular location, the nearest location is the object whose information is to be visualized.

However, although this already achieves, to some degree, the Object Identification requirement, it is still not enough to display the information correctly on the screen. It is for this reason that the application also calculates the landmark's azimuth angle. The application gets the co-ordinates of the POI and forms a right angled triangle between the user's location, a point directly in front of the user projected on the plane that the POI is on, and the POI location itself. Using conventional trigonometric functions the azimuth angle is calculated and the system would know whether to display information on the screen or not depending on the resultant azimuth angle.

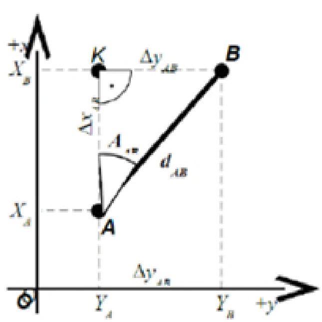

Figure 2. Calculation of Azimuth Angle in principle. If A is where the device is and B is the landmark, then the azimuth angle is the angle between AB and AK.

In this manner, the application is able to perform Object Identification quite effectively. When an augmentation is indeed triggered, a marker appears on screen showing the landmark together with the relevant reviews.

Figure 3. Output of the Visualization Component where the landmark is pointed out by the icon appearing at the center of the view, and the landmark name and any reviews are displayed at the bottom.

VI. RESULTS AND EVALUATION

In order for the system and methodology of this study to be evaluated properly, a number of different aspects were analyzed. The first tests were carried out in order to analyze the performance of the system's personalization capabilities, more specifically, the system's ability to generate accurate user profiles representing its users. In order to complete this evaluation, a number of individuals were invited to participate in the process. Through this crowdsourcing, data could be gathered which would in turn mock a real world scenario where the system would be deployed, and the system's performance could then be analyzed.

The second tests carried out focused more on the general deployment of such a system to a wearable device and how would the general public, when given a wearable device that performs in this manner, reacts to its use. This evaluation focused on the complete package that includes both the personalization components, and the landmark detection and Augmented Reality components of the system, and again involved the participation of a number of users

A. Crowdsourcing demographic analysis

In order to determine the quality of the relevance of the data obtained through crowdsourcing, and thus evaluate the completion of both objectives, it is essential to analyze the background of the test subjects that provided it. Sixty people were invited to participate in the evaluation through completion of the questionnaire. The information extracted from the demographic part of the questionnaire, consisting of age and the user's perceived level of use of social media, was thus extracted and analyzed.

As can be seen from the charts in Figures 4. and 5., the majority of the participants were between 20 and 30 years old. The people belonging to this age group are considered to be the most avant-garde when it comes to trying out new technologies and are also the most active on social media [10]. Therefore, they provide an ideal basis on which to build the evaluation. However, other age groups were also taken into consideration in order to evaluate the system's performance according to different user behavior.

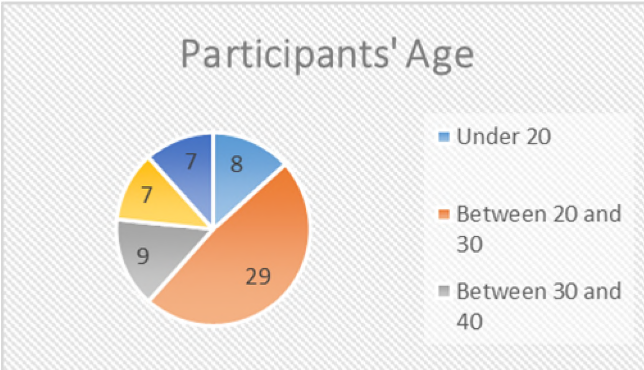

Figure 4. Pie chart showing age distribution between participants in this study. (Source: Luca Bondin, Intelligent Wearables)

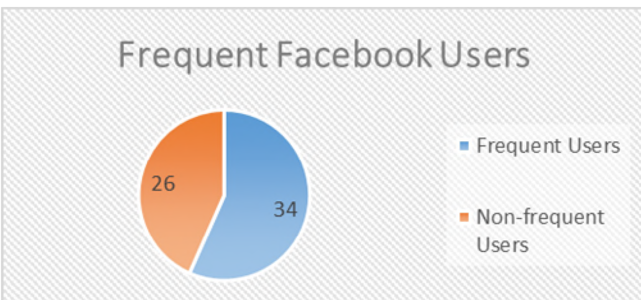

Figure 5. Pie chart showing distribution of participants according to perceived use of Facebook (Source: Luca Bondin, Intelligent Wearables)

As for the test users' level of use of social media, the questionnaire asked users whether they consider themselves as frequent Facebook users. 34 respondents said they were regular Facebook users while the remaining 26 said otherwise. This distribution was ideal as while the system and the methodology could be evaluated on profiles that are regularly updated, it could also be evaluated on other profiles whose owners do not share as much information frequently.

B. *Profiling accuracy analysis*

In order to complete the evaluation of the profiling components of the system the participants were first asked to explicitly mark which of the interest fields they thought best described their interests. Next, they were asked to make use of the system, through the aforementioned web agent, that makes use of the system's scripts to extract the participants' social media profiles and generate a user profile accordingly. The generated user profile is then compared to the interest fields marked by the user. Given the set-up of the system and what the system is aiming at achieving, it was decided that calculation of Precision and Recall values was the optimal way of evaluating the accuracy and suitability of the system for the purpose it is intended. Finally, F-Measure is used to provide a single measurement for the system.

The average Precision rate obtained by the system was 0.81 meaning that there is an 81% chance that the system will at least classify the user into one correct category and return relevant suggestions. On the other hand the Recall values returned by the system were somewhat smaller. Although the highest Recall value achieved is 1.0, the average Recall value obtained stood at 0.60 meaning that there is a 60% probability that a relevant interest field is found in the user profile. Again these results may have been compromised with previously mentioned issues with users not sharing information which is entirely relevant and indicative of their interests. Surprisingly though, the system still performed reasonably well in cases when the test user listed down that he or she was not a frequent Facebook user. Therefore, one may speculate that rather than being a case of whether a user is making frequent use of his profile or not, it is rather the case of what content the user decides to share through the social media profile. The average f-measure value obtained from the conducted tests stands at 0.65.

TABLE I. THE RESULTS AFTER EVALUATION

	Minimum	Maximum	Average
Precision	0.33	1	0.81
Recall	0.17	1	0.60
F-Measure	0.29	1	0.65

C. *System Design Evaluation*

The second evaluation included the evaluation of the system as a whole and how people would react at being given the opportunity to use such a system. In order to complete this evaluation, the participants were presented with a scenario where such a system could be deployed on a wearable device, and were presented with the system's abilities when making use of it. The participants were then asked a number of questions to determine whether they would make use of such a system, whether they would feel comfortable using such a system due to issues that may arise with the way the system is designed to work, and finally whether they think that such a device would truly enhance their visit to a city and why.

The results for this evaluation are overwhelmingly positive. All the participants think that such a system does indeed enhance one's visit to a city and would indeed be willing to use such a device should it be given to them. While some mention that such a device would allow them to roam freely without following tours, others mention that such a device would render their lives easier in the sense that it reduces the need for them to do endless research before going on their trips. This trend is evident amongst all age groups. However, some issues do seem to exist as people of all ages are becoming more conscious of what information they share and who they share this information with. These issues arise due to the system's use of a user's personal data. A number of people express their concern at such systems requiring, and eventually extracting, personal information from their social media profiles to achieve their functionalities.

Upon analysis, the results obtained provide further indication that the objectives set out at the start were indeed reached. For the purpose of this implementation the efficiency of implicit data gathering could be deduced from the results obtained through the evaluation of the personalization components. This evaluation shows that taking into consideration the various limitations that exist, especially with the user data, the implementation still yielded satisfactory results, most notably through the fact that the system provided suggestions for all the test profiles. There were occasions where it managed to profile the user perfectly. On the whole, the 81% precision rate was quite good, although the recall rate achieved was slightly disappointing. As mentioned, there are quite a good number of variables that may in fact influence these results and all in all, considering the effort done in trying to overcome any issues that the approach adopted might have, the results obtained were satisfactory. Certainly, with more uniform information fed to the system to perform personalization, the results are bound to improve even further.

VII. Future Work

More work could be done to improve the performance of the system with respect to its personalization capabilities, more specifically, to improve on the Ontology-based approach adopted in this study. The first issue that should be tackled is the cold-start problem that the system might encounter when working on some profiles. This problem could be tackled by looking at alternative sources through which it could acquire data for personalization, which may be other social media platforms or through mild forms of explicit data gathering. Also, the use of a hybrid approach to personalization would perhaps be ideal. At the moment, the system performs profiling by performing comparisons between words and their synsets to the interest fields and their synsets, but what if the system could analyze whole sections of data and know what they actually are? For example, if a person writes about some football team then the system knows that what the user has written about is actually a football team and it determines that the user is interested in sport without actually finding the exact word "sport" or a word pertaining to its synset.

Boosting the personalization capabilities of the system could also be achieved through obtaining more information about the user from other sources. There is a reluctance to move towards explicit data gathering but the need for better input data is clear. This can be achieved from other sources such as a user's browser history and from some form of mild explicit data gathering.

Secondly, work could be done to improve both the Augmented Reality approach of the implementation as well as some minor tweaks that make the implementation work more intelligently such as the ability for the system to know in which city it is at a point in time, and automatically make calls to the Google API and update the landmark database with landmarks that are in the vicinity. Also, the Location-based approach could be strengthened with an implementation of computer vision methods in order to improve performance.

Finally, when the hardware is available the system should be deployed on a wearable device that could satisfy the system requirements and allow it to operate at its full computational abilities.

VIII. Conclusions

The approach chosen for implementation was able to produce a system that can profile a user to a reasonably high degree of precision. The rule-based approach, aided by traits derived from both the weighted key-word profile and the ontology-based approach to personalization systems was pivotal in achieving the set objective, and the 81% Precision rate and 60% Recall rate prove the efficiency of the said approach. A definite strong point of the system is however its flexibility of the system in terms its structure and the way it is intended to work. As shown from the evaluation results, such a system deployed on a wearable device would greatly enhance a person's visit to a new city, increasing both accessibility and comfort, while the fact that it is able to be deployed in any city around the world with the same performance results sets it apart from other systems of its kind.

This study opens the door to a better understanding on how intelligent systems that are designed to work on a wearable device may be implemented, which is a positive step in the development of such devices which are becoming ever more popular and essential. Along with improvements on the approach taken and future work cited, such a system would be both revolutionary, as well as provide an innovative solution on how such systems could be developed to act intelligently with respect to the user's ever changing demands.

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