Graduate Seminar Assignment 2

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***Abstract*—This is a survey project report about various research projects I have chosen to survey in Mobile, Wearable and Ubiquitous Technologies. To be more specific, these papers focus on "Human Centered Computing" where they further focus on "Interaction Techniques".We will focus on various papers that focus on understanding between human beings with the design of computational artifacts.**

***Index Terms*—Human Centered Computing, Interaction Techniques, survey report, mobile technologies.**

I. Introduction to Human Centered Computing

Today, computers are leading the revolution.They have significantly changed the way we communicate and interact with each other.Not only this, they have changed the way we work, the way we play and even the way we build our homes.We can rightly say that computers have transformed every aspect of our daily lives.But the major problem with present computing technologies is the fact that many of these technologies are unfriendly,unnatural or weird,clunky and even difficult to use.This creates more complexity rather than making our lives simpler as expected. The main reason behind this can be the fact that most of the new technologies are done by companies or individual researchers that are isolated from the general public. This isolation can create some "awkward" interactions between the end user and the device and the product may turn out to be less popular as expected even though it may have the most up to date technological advancements and features. Here is where HCC(Human Centered Computing) comes into light. Human Centered Computing is a set of methodologies that apply to any field that uses computers in applications in which people directly interact with devices or systems that use computer technologies. All the researchers and designers working under Human Centered Computing have vast experience in various fields like computer science , sociology ,psychology etc.Research on HCC have been carried out since 1990s.While some researchers focused on understanding human psychology and interaction methods, others have focused on creating strategies that work better for computer device and interactions with them.We can consider HCC as a specialized subset of HCI(Human Computer Interaction).HCC specializes in a way that while we have to focus on the mass public, how they interact with the technology individually and generally, socially and culturally, we also have to take into account how they react for specific situations which makes the task more complex.The single most important factor in HCC is how we represent the input-output communication via device sensors and digital media respectively.We can thus say that for HCC we expect computing system to be:-

- Multimodal,i.e, processing inputs and outputs in a naturally rich communication channel.
- Proactive,i.e, understanding cultural and social contexts and responding accordingly.
- They must also be available to a wide range of users outside the desktop

II. Research in Human Centered Computing

An important factor of human centred computing research is how we analyse the multiple input multimedia signals at perspective,cognitive and affective level .We have to take into account certain factors like emotion, attitude and attention. Research on machine learning with domain knowledge and data mining will play an important role in this field [1]. Further research in human psychology and quantification of human related knowledge is required to create mathematical models that can be integrated into multimedia systems.We will also require integration of sensors,humans and media which takes humans as a central subject.Generation of more human-centred data which can be used for training models.Finally we can not overlook the privacy issues which may also contain ethical and cultural issues.

III. Brief introduction to papers surveyed in this report

SenCAPTCHA: A Mobile-First CAPTCHA Using Orientation Sensors [2]

CAPTCHAs are used to distinguish between human- and computer-generated online traffic. In recent years there has been a large increase in the amount of mobile traffic which has created the need for an efficient mobile traffic verification system. This paper focuses on implementation of orientation sensors to verify if the user is a human or a bot. By bot we refer to autonomous Internet programs and scripts that are widely used by websites to gather data.However, 55% of bot traffic is malicious [3].By malicious intent we can give example of comment spamming, password guessing attacks or click fraud. To fight against these bots, CAPTCHA(Completely Automated Public Turing test to tell Computers and Humans Apart) was proposed in 2000 [4].

Types of CAPTCHA

Google's NoCAPTCHA: Google's reCAPTCHA(i.e, NoCAPTCHA) uses information regarding user's network connection, browser settings,cookies and previous browsing behaviors to minimize user interaction in verification.But due to technical limitations like deleted cookies or disabled JavaScript causes the verification to fall back to traditional CAPTCHA [5].

Text-Based CAPTCHA: Text-based CAPTCHAs are also widely popular as they are tougher to read by bots using OCR(Optical Character Recognition).A lot of research has been done to make such captchas more difficult to read via OCR.But in recent years, Deep-Learning based approaches having 90% accuracy in reading such CAPTCHAs [6]. Audio-Based CAPTCHA: Another type of CAPTCHA particularly suitable for visually impaired individuals but they require a large dataset of audio data in different languages.

Video-Based CAPTCHA: Considered superior to static text and image based CAPTCHAs, the first video based CAPTCHA was released by NuCAPTCHA in 2010 [7].Although, the verification system was defeated by Moving-Image Object Recognition(MIOR) techniques.Also, downloading large amount of video data may hinder with user experience and also be unpleasant for mobile users with limited bandwidth.

Image-based CAPTCHA: These CAPTCHAs require the user to solve image labeling by selecting pictures of certain objects or animals which may be distorted or not clear.Computer-vision based algorithms have been successful in breaking these systems.

SenCAPTCHA

Authors of this paper have introduced a mobile-first CAPTCHA that uses mobile device orientation sensors to verify users.The design of SenCAPTCHA was inspired by 3 main qualities:-

- Low Effort
- Enjoyable
- Clean UI

Overview

The CAPTCHA is verified by the user by tilting the phone to direct the ball to the eye of the animal shown in the picture.SenCAPTCHA works in a client-server model. It has two components,a server-side component that determines when the CAPTCHA is solved, this may depend on several factors like ball trajectory or speed.The other component is client-side component that displays the UI and handles the sensor-reading part and sends the data to the server.The most important separation is the fact that the client side never knows the location of eye which may be exploited by the attacker.

Methodology

SenCAPTCHA's workflow can be divided into three primary functions.These are:

- Initialization
- Ball's movement
- Trajectory Analysis

An overview of each of these three functions is provided.

Initialization: During the initialization phase, the server creates a puzzle image, creates the starting position of the ball with respect to its distance from the target(eye of the animal) and sends all of this information to the client to render the user interface of the puzzle.For creating the puzzle image, the server first randomly picks an image from the database, then modifies the image in one of the three proposed techniques:

- **Rotate**: the image is simply rotated at a random angle.
- **Zoom and Translate**: in this method, the image is first scaled horizontally at a random factor and then scaled vertically randomly.
- **Tile**:another successful method is to break the image into several tiles and then rearrange those tiles randomly and show it to the user.

After the mutation, the server will also record the new location of the target(i.e, eye of the animal).These mutations can be used to create many unique puzzles dynamically.For example, if in the Tile method, if we break the image into nine tiles and randomly rearrange them, we will get 9!=362,880 possible combinations. Next, the server calculates how close the ball should be to the target to mark the puzzle as solved.The equation to do so is given as:

$$d = tolerance + \frac{width+height}{2}$$

Where "tolerance" is the value that determines how close centers of the ball and target should be to mark the puzzle as solved. Also a random starting position is initiated and finally the server sends the mutated image,ball's starting position, radius of ball(d) to the client that handles the data and further displays the mutated image to the user.

Moving the Ball: To move the ball, the user tilts the phone in desired direction. Azimuth-pitch-roll convention is used for measurement of device's orientation angles.Only the pitch and roll angles are required for moving and computing position of the ball.The pitch angle denotes values between -180° and 180° while roll angle reports value between -90° and 90°.Each time the ball moves by a single pixel, a updated location is sent to the server which continuously checks whether the puzzle has been solved.Another added feature is that unlike other CAPTCHAs, where user need to click on submit button, here the user simply hovers the ball over the target to be redirected to the desired web page.The movement of ball is constrained to boundaries of the image.If the users fails to complete the puzzle within a given time period like 1 minute, they are considered to have failed the CAPTCHA.

Trajectory Analysis: After the ball has reached the target(animal's eye), the server will then determine, by the ball's trajectory, if it was completed by a human or a bot. It is expected that humans tend to naturally move the ball towards the target smoothly while in case of bots, they will need to use certain searching strategies to move the ball in desired location which will make the trajectory unnatural.We can further distinguish human from bots by comparing the user trajectory with the optimal trajectory,which is usually a straight line from ball's starting position to the target.

Conclusion

The project looks very promising for user verification.The authors have provided an alternate use of orientation sensors present in modern smartphones and mobile devices.This can also be very useful for smaller displays like smart watches where the screen estate is very limited, showing a simple image on the smartwatch with the ball is much more intuitive than showing grid of images to select from.Overall, the project is very interesting and definitely worth researching more about.

SCRATOUCH: EXTENDING INTERACTION TECHNIQUE USING FINGERNAIL ON UNMODIFIED CAPACITIVE TOUCH SURFACES [8]

Overview

Capacitive touch surfaces used in smartphones,laptops and touchpads are one of the most popular pointing devices.These touch inputs can be multi-dimensional [21], but present touch surfaces do not exploit this fact.Thus, many research has been done on creating new input approaches like using pressure force [22],shear force [23], [24],touch with a knuckle [25], hand contact shape [26], or different areas of the fingerpad [27].While being very useful in input space, these methods require additional sensors or attachments. In this paper, the authors present a new interaction technique using fingernails.With fingernail detection on capacitive touch screens, we can add more input functionality to touch screens like command invocation and mode switching.The main reason authors worked on the concept was due to the fact that fingernail detection from fingertip requires only tens of milliseconds of shunt current data, thus making the switching process seamless.The authors propose certain advantages of using ScraTouch like:-

- Simple Algorithm
- Short processing time
- Simple operations
- Robust recognition

Methodology

The main principle behind fingernail detection from a fingertip is the fact that they both are made up of different physical materials.Thus, they are able to produce distinct electrical signals when in contact with a touch (input)surface. To be further specific, they are able to produce distinct shunt current. Every capacitive touch screen uses shunt mode sensing to detect finger touch. It has a transmission electrode(Tx) and receiving electrode(Rx) groups that are orthogonal to each other.When a finger touches the intersection between Tx and Rx,a shunt current is created from Tx to the Ground(GND).The amount of shunt current determines if the screen was touched or not.ScraTouch uses a simple algorithm to detect the different shunt currents produced by the fingertip and fingernail.

Applications

The paper states many applications of ScraTouch but I personally think this implementation has the most potential in reducing "repetitive" motions.The most popular application would be eraser feature in scribbling apps.We do not need to hover over the eraser button to switch the mode and come back to the intended position.We can simply erase the contents of the screen by using our fingernails.Also we can invoke OS level functions by simple touch of our fingernail which will open submenu so we can modify the data accordingly.

TRACKING DEPRESSION DYNAMICS IN COLLEGE STUDENTS USING MOBILE PHONE AND WEARABLE SENSING [9]

Overview

This paper focuses on the rising rate of depression cases in college campuses.The authors have proposed using mobile sensing to track mental health of students continuously.The authors present results from a study of 83 undergraduate students at Dartmouth College across two 9-week terms during the winter and spring terms in 2016.The paper specifically discusses the following findings:-

- The proposed set of passive sensors based symptom features are derived from phones and wearables which are further used to measure 5 major depressive disorder symptoms.
- The authors find a number of correlations between proposed symptom features and Patient Health Questionnaire(PHQ-8), which is used to measure depressive disorders in large clinical studies.
- Certain findings were observed such as students more depressed usually:
  - Were more likely to use their smartphones more particularly in study place in comparison with all day phone usage.
  - Have irregular sleep schedules.
  - Spent more time being stationary.
  - Visited fewer places during the day.
  - Are around fewer conversations.
  - Sleep for shorter periods.
  - Go to sleep later and wake up later

Overall, the authors present a case study that captures depression dynamic across the term, where student's depression is elevated as the term progresses which is indicated by less sleep, less conversations, and fewer places visited.But there is a point when a student shows resilience and recovers from his depression.

Methodology

To assess depression the authors use the same depression screening tools and principles that have been used since the last 30 years [10].With the combination of a mobile app and wearable, certain activities of students are recorded to track depression dynamic, they are:-

- **Sleep Changes**: A student may experience insomnia(difficulty sleeping) or hypersomnia(sleeping too much) with changes in sleep schedule.This is oftentimes due to the demanding terms which include activities like assignment due dates, exams, social life, sports, etc.
- **Diminished ability to concentrate**: This is primarily tracked by frequency phone unlocks.previous research has shown correlation between smartphone usage and depression and anxiety [11].The student appears distracted, unfocused often when not performing well.The authors discuss how using a phone in classroom are signs of diminished concentration in comparison to using phone in social spaces, dorms , gyms or even walking around the campus.We can differentiate these usage types by using phone location data and contextual labelling of campus [12].
- **Diminished interest or pleasure in activities**: We can track this by checking time spent at different types of places on college campus.We can primarily distinguish places as study areas,classrooms,library,gym,social and cafes.
- **Depressed mood and Fatigue or loss of energy**: This is measured using wearables by tracking heart rate of students.Research shows heart rate is associated with depressed mood [13] and fatigue [14].

SmileAuth: Using Dental Edge Biometrics for User Authentication on Smartphones. [32]

Overview

User authentication is an aspect of privacy and security in smartphones. In various research it has been shown that certain authentication systems like fingerprint [15] and facial recognition [16] systems can be broken by various methods.Fingerprint films can be used to compromise fingerprint-based authentication [28] and prosthetic masks [29] have been known to be able to break facial recognition authentication.Password,Pin or draw pattern on the other hand, have risk of being peeped [30] or stolen [31] by attackers. So in this paper the authors use unique features to authenticate users using dental edge biometrics for reliable user authentication.The authors use dental features like to tooth size, shape, position and surface abrasion to achieve up to 99.74% accuracy.SmileAuth is unique enough to distinguish between twins using dental edge biometrics.Authors of this paper had the following conclusions:-

- The authentication model was Able to prove that dental edge biometrics are unique across different users but table for the same user.
- The authors also propose a method to accurately estimate the camera angle of the image so that the authentication model can be produced in practicality.
- The authors created a prototype of SmileAuth and did extensive experiments on 300 volunteers and showed that SmileAuth achieved an average of 99% accuracy.

Methodology

Previous work has been done in dental biometric authentication Where two factor authentication approach was used in which both user teeth image and user voice was used [17].However this work only used coarse-grained feature matching using dental biometrics. SmileAuth exploits the fine-grained dental edge lines as features and performs angle-based feature matching using multiple consecutive images.The model created in this paper has the following workflow:-

- Image Collection
- Image Preprocessing
- Dental Feature Extraction
- Similarity Threshold Calculation
- Feature matching
- Authentication Success/Failure

Tap-to-Pair: Associating Wireless Devices with Synchronous Tapping [18]

Overview

With increased popularity in Internet of Things(IoT), there has been a surge in wireless devices people use in their daily lives.Most of these devices are connected via Ad-hoc pairing.These devices can be separated into two types, Scanning devices(Scanners) and Advertising devices(Advertisers).While Advertisers like bluetooth speakers and wifi routers broadcast their identities over the air, Scanners like smartphones and laptops send connection requests to such advertisers.But before scanners sends the request, the user needs to manually associate these devices(called device association [19]).Presently, this is done by the user by navigating to a list of available advertisers on the scanner's screen and selecting the intended advertiser.This directly impacts the pairing experience.This method is certainly unpleasant if there are too many advertisers present in the scanner's environment, which will create a long list of available advertisers and user will have to browse through the list to find the intended advertiser. Another pain point of this pairing method is the fact that this method is only initiated by the scanner even though it would be much more convenient if we could initiate the process via advertisers, which are usually more light and portable for the users.

Thus, in this paper the authors propose Tap-to-Pair, which, as quoted in the paper, is defined as "A spontaneous device association mechanism that enables users to initiate association using off-the-shelf advertising devices without hardware or firmware modifications." There are two major advantages of using Tap-to-pair are:

- To implement the technology, the requirements of resources are minimal.The authors simply use the built-in antennas present in the advertisers to create signal

changes.For scanners, we only require a binary display and a recognizer.Even the most basic LED can be used as binary displays to associate the devices.
- While many are focusing on creating advanced interfaces on the scanner display to associate and pair the devices, Tap-to-Pair focuses on providing seamless association of advertisers of various size,cost and power constraints.

In the final evaluation study, the authors implemented Tap-to-Pair on a chip and were able to associate devices with a successful pairing rate of 93.7%.The contributions proposed by this paper are as follows:

- The paper proposes a novel association mechanism for scanners and advertisers by synchronous tapping with no associated hardware or firmware modification.
- The authors conducted user study to determine its practical potential.
- The paper also proposes four potential applications for Tap-to-Pair.

Methodology

The authors do so by tapping on an area near the advertisers antenna. This creates a change in transmitted signal strength from the advertiser which can then be detected by the scanner. This change in transmitted signal strength can be leveraged for associating the devices by synchronously tapping near the advertiser's antenna with the blinking pattern displayed by the scanner. An example would be tapping on a bluetooth mouse synchronously with the blinking pattern displayed on the laptop's screen.The scanner then first acts as a recognizer to record the correlation between the two signals and if successful, send an association request to the target advertiser. To be more specific, the sensing mechanism is implemented on a simple principle of signal modification of the adviser by hand[20].A "tap" event can be detected by a large signal drop.A "release" can be detected by a corresponding signal increase and a "hold" event can be detected by a relatively small signal variation after a tap or release event. These events can be represented in form of simple binary code.The binary digit "1" represents that the user's hand and device are in contact while "0" means that the hand is not in contact with the device.We can then define a "tap" event as a transition from "0" to "1" and a "release" event as a transition from "1" to "0". We can then create a blinking pattern by repeating the code.For example, the repeated tapping pattern(single tap represented by "01") can be represented as "01010101...".Another example would be differentiating between single tap("00001") and double tap("01011").

Applications

The paper proposes four potential use-cases for Tap-to-Pair:

- **Stylus**:Often, a stylus is shared between multiple computing devices when collaborating.Presently, users have to disconnect the stylus from the connected device to connect it to other devices which can disturb the workflow.Tap-to-Pair would work with such devices seamlessly to provide better pairing experience.
- **Wireless Speakers**:Presently, users have to use a remote interface to connect the wireless speakers to various devices like smartphones or televisions.Tap-to-Pair can make the switching process seamless by giving the speaker the control to choose the device it wishes to switch to.
- **Wireless Printers**: The main advantage of using Tap-to-Pair in such devices is that while present printers require NFC(Near Field Communication) enabled smartphones to connect to the printers, Tap-to-Pair works readily with both Bluetooth and Wifi-Direct devices, which are present in most smartphones and laptops.
- **Wireless Rings**: The main limitation of Wireless rings is the fact that it has limited hardware due to its size.Tap-to-Pair can use common technologies like bluetooth which are again commonly present in such devices.The user can then tap the ring by his/her thumb as a mode of input.

FINGER GESTURE TRACKING FOR INTERACTIVE APPLICATIONS: A PILOT STUDY WITH SIGN LANGUAGES [33]

Overview

This paper introduces a method to explore feasibility of finger gesture tracking using a single sensor placed on the finger as a ring and a smartwatch worn on the wrist.The authors present a new system called FinGTrAC(Finger Gesture Tracking with Application Context) to track finger gestures.A sign language is a way of communication where words are expressed in the form of body motions and facial expressions instead of speech.The authors have focused on using American Sign Language(ASL).The paper shows successful detection of 100 most frequently used ASL words [34] using FinGTrAC. Prior work has been done via wearable based approach and camera based approach.Wearable based approaches were only limited to a few tens of gestures [**?**], [**?**], [**?**], [35]. Camera base gestures track full finger motion, but they are heavily dependant on lighting/resolution as well as presence of the user in the camera view.FinGTrAC proposes to overcome all these limitations by using just two sensors to detect sign language by using application context.The authors propose following contributions in this paper:

- FinGTrAC is the first device to use only two devices/sensors to detect ASL sign language using application specific context.
- The system requires only a low fidelity training from a single user which then scales the gesture recognition limit to hundreds of gestures in comparison to tens of gestures of previous wearable methods.
- FinGTrAC systematically combines data from sensors in context of an ASL sentence into a Bayesian inference model for high accuracy sentence decoding.
- Implementation is done on user-friendly platforms of smart-ring and smart-watch for detection in real time.
- A study with 10 users showed an accuracy of 94.2%.

Methodology

A user would wear a smart ring on the index finger (index finger is the most involved finger in ASL finger gestures), and a smartwatch on the wrist.y. The Inertial Measurement Unit (IMU) sensors (accelerometers, gyroscopes, and magnetometers) on the smart ring and smart watch are used for finger tracking, and the results might be displayed on smartphone screen, or read out on speaker. To be more specific, the hardware used for this project were:

- An off-the-shelf button shaped sensor(VMU931 [39]) worn on the index finger like a ring .
- SONY Smartwatch 3 SWR50 worn on the wrist.
- An edge device(desktop) that continuously received data from previous two devices.

The edge device was able to decode the sentences in real time. Some of the core technical modules were as follows:

- Data Segmentation:ASL sentence is comprised of sequence of words.Given a sequence of words, we can distinguish the data into two phases,i.e., “word phase”, where the user is expressing a word by hand signal and “transition phase”, where the user is transitioning from one word to another. There is a “dip” in sensor signals when it detects transition phase.We then create a “dip template” and then perform a pattern matching with Dynamic Time Warping(DTW) [40] method.
- Preprocessing:We need to preprocess the data to improve robustness of word detection because different users perform ASL signs differently from each other.The paper does so by passing the sensor data through a low pass filter to remove any noisy data above 10Hz.After this, we use “Elimination by Periodicity” to eliminate words from dictionary that do not match with the number of peaks created due to periodic signals generated by sensor data which creates unique peaks for different words.
- Word Gesture Recognition and Ranking by DTW: DTW is a pattern matching technique that inspects the overall shape of two signals to determine their similarity.
- Sentence Decoding with HMM and Viterbi: The top 10 matches for each word from DTW are further processed with a Hidden Markov Model (HMM) to improve the accuracy. The HMM, particularly, incorporates wrist location transitions between words in the context of a sentence to decode the most likely sentence.We will then use Viterbi algorithm [41] to efficiently select the sentence assumed by HMM with most likely probability to be correct.
- Finger-spelling Detection: Finally, we only use the index finger sensor to detect the character being expressed as the wrist sensor does not correctly distinguish certain characters.

We then put all of these functions into the model and create a workflow to convert the sensor data into an ASL sentence.After creating the model, the authors did a systematic user study with 10 users shows a word recognition accuracy of 94.2% over a dictionary of 100 most frequently used ASL words.

IV. Final Thoughts

After going through all the papers in Human Centered Computing, I can personally say that a lot of credible work has been done to upgrade the computation focused interactive techniques dynamics.The papers also emphasize the fact that a lot more work can be done in this field. As I am having previous mobile development experience, I am a bit inclined towards mobile computation and believe that with increasing computational power of new generation mobile devices, one can really do many unique research in the field of Human Centred Computation with mobile technologies in focus.I personally wish to work more in this topic for future research work where I can utilize smartphone sensors to create an interesting application as I believe that mobile sensors are still under-used for mass utilization.

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