KissGlass: Greeting Gesture Recognition using Smart Glasses

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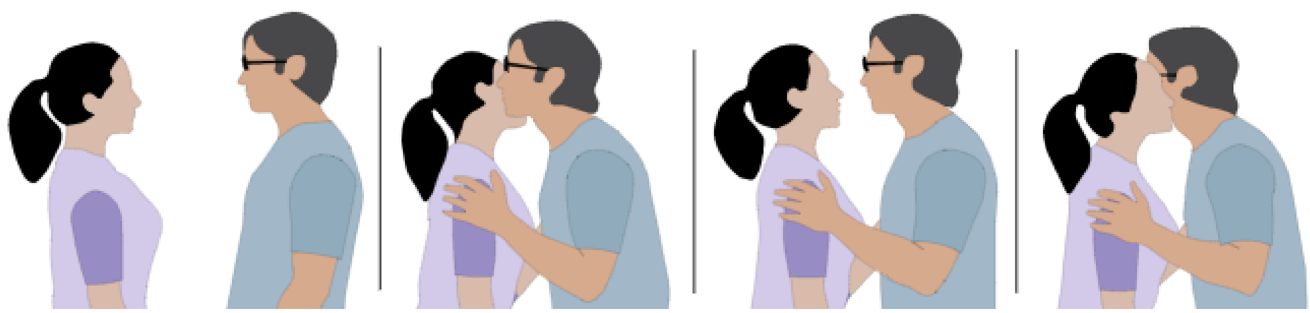

Figure 1: Cheek kissing is a common form of cultural greeting in many European and African countries. However, there are many parameters of how to perform the gesture, including starting on which side and how many times. These parameters can often be an indicator of the person's context, such as his or her location or perhaps the gender of the person's partner.

ABSTRACT

Cheek kissing is a common greeting in many countries around the world. Many parameters are involved when performing the kiss, such as which side to begin the kiss on and how many times the kiss is performed. These parameters can be used to infer one's social and physical context. In this paper, we present KissGlass, a system that leverages off-the-shelf smart glasses to recognize different kinds of cheek kissing gestures. Using a dataset we collected with 5 participants performing 10 gestures, our system obtains 83.0% accuracy in 10-fold cross validation and 74.33% accuracy in a leave-one-user-out user independent evaluation.

CCS CONCEPTS

• **Human-centered computing → Gestural input**; *Ubiquitous and mobile devices.*

KEYWORDS

gesture recognition, greeting gestures, smart eyewear, smart glasses

ACM Reference Format:
Richard Li, Juyoung Lee, Woontack Woo, and Thad Starner. 2020. KissGlass: Greeting Gesture Recognition using Smart Glasses. In *AHs '20: Augmented Humans International Conference (AHs '20), March 16–17, 2020, Kaiserslautern, Germany*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3384657.3384801

AHs '20, March 16–17, 2020, Kaiserslautern, Germany
2020. ACM ISBN 978-1-4503-7603-7/20/03…$15.00
https://doi.org/10.1145/3384657.3384801

1 INTRODUCTION

Human-computer interaction (HCI) is primarily concerned with studying how humans interact with computers. One way of extending that definition is in exploring how computers can be used to facilitate interactions between humans. To that end, the HCI community often conceives of new gestures that can be robustly recognized by a computing system. On the other hand, humans have spent centuries developing gestures for communicating greetings and intent, such as hand shaking or finger pointing. One particular gesture, kissing the cheek(s), is common practice as a greeting in Europe, Africa, and South America. However, how the kiss is performed varies between locations and can be an indicator of different contextual factors such as the gender of the person receiving the kiss as well as the formality of the interaction.

The last couple of decades have seen many smart glass devices developed and evaluated in academic settings, and they have recently become mainstream with commercial offerings due to recent advances in technology enabling them to look increasingly more like normal glasses. While they have primarily been used as platforms for providing feedback to the user (i.e., through a display in the lens or with bone conduction speakers in the earpieces), smart glasses are also convenient for deploying sensors such as cameras, inertial measurement units (IMU), or electroencephalogram (EEG) electrodes for a variety of interaction and well-being applications. Snap Spectacles are sunglasses-form factor devices that include two cameras for recording 3D video [4]. Level smart glasses enable activity tracking with a 9-axis IMU [2]. The Lowdown Focus glasses

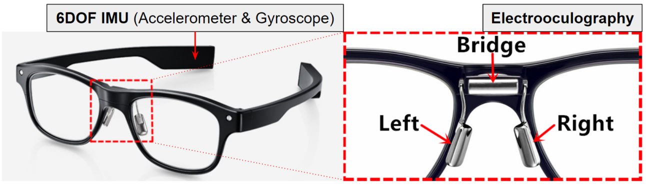

Figure 2: The Jins Meme smartglasses and its EOG sensor placement. The IMU is at the end of the right leg.

by Smith use EEG electrodes at the nose bridge and behind the ears for monitoring brain activity [3].

In this work, we demonstrate the ability to recognize different types of cheek kissing, enabling a technique for passively sensing physical and social context. The sensed context could then be used for automating a number of digital actions. For example, if the system detects that the user has performed a greeting gesture, then it can automatically pause the user's music to allow the user to fully engage with their partner. Similarly, detecting a greeting gesture corresponding to a particular country can turn on an automatic translation tool set to that country's language. Another use case is to passively build a diary of human interactions. This application would operate by capturing a photo of the companion's face whenever a greeting gesture is recognized. These automatic digital actions, initiated by passively sensed signals that are already used to denote the beginning of a social interaction, will help users to remain engaged in the physical world.

To more concretely describe our work, we enumerate some of the different variations of the kiss greeting gesture:

- In most of Spain and Portugal, a kiss on each cheek, starting with the right cheek is standard.
- Italians follows a similar convention, although they prefer to start with the left cheek.
- In the Netherlands, cheek kissing begins on the right, and they go right-left-right [5].
- Belgians also give three kisses, but only if the receiver is older. Otherwise, they only give one.
- In France, the number of kisses given ranges from 1 to 4, and which side to start on, all based on the specific area [7].
- In the United Arab Emirates or other Arabic countries, the greeting is performed with a nose kiss which is called 'Khashmmakh', in which two people bump their noses together [16].

To account for the wide variety of gestures possible, including those described in the examples above, our work attempts to recognize all combinations of number of kisses and sides to start on, treated as a standard gesture recognition problem. We present the motivation of understanding physical and social context and potential ensuing applications as the long-term goal.

2 RELATED WORK

To provide background for this research, we briefly describe similar work in wearables, gesture recognition, and facilitating human interactions.

2.1 Wearable Sensing

Wearables are, by definition, typically worn close to the body, which can enable convenient, always-available interactions. Many wearable devices offer a number of interactions by leveraging IMUs for sensing finger [29] and hand [15] movements. In addition to the hands, other systems have enabled interactions by tracking tongue movements using capacitive touch sensors for silent speech [20] or by placing pressure sensors in the soles of shoes for tracking foot movements [10]. In addition to facilitating interactions, wearables also offer the opportunity to passively collect data for understanding human activities and context. IMUs have been used to track eating episodes [6], and pressure sensors positioned in shoes have also been used to track exercise activities [24]. Our work bridges these two similar areas by leveraging the recognition of cultural gestures as a means of passively understanding context.

2.2 Gesture Recognition with Smartglasses

Humans wear eyeglasses for a number of reasons, including fashion, correcting eyesight, and blocking sunlight. As an already accepted accessory for the body, eyeglasses can thus provide a convenient form factor for instrumentation. Additionally, the face is a very expressive part of the body, with many signals reflecting conscious and subconscious cognitive processes. Electrooculography (EOG) [27], EEG [28], and photo-reflective sensors [19, 23] have been used to track facial movements and gestures. Such facial gestures might be used to control devices on-the-body or in-the-environment [21]. Detecting the interaction of hands on the face [17, 22] or on a face-worn device [12, 18], have also been proposed. Tracking different physiological features of the user in free living conditions has been another significant area of research. Eye blink tracking [8, 13], reading detection [14], eating detection [30] and recognizing fatigue [31] are all common target activities for smart glasses to recognize. Our work builds upon this literature to detect a new class of activities which represent the social context of the user.

2.3 Facilitating Human-to-Human Interactions

Humans are social creatures, relying on interacting with other humans for survival tasks such as finding food and companionship. Technology has a long history of keeping humans in touch, even when they are not in physical proximity. Written language led to writing letters, which can be transmitted over long distances. Phone calls allow humans to speak to each other. Photographs and video chatting enable people to see each other from far away.

There is significant academic work in exploring further ways of facilitating human-to-human interaction. A number of works have explored sharing uncommon sensory modalities, including tactile [11], olfactory [9], and breath and heart rate [25]. Our work contributes to the space of facilitating human-to-human interaction by potentially automating many digital actions, allowing users to stay engaged in the physical environment.

3 KISSGLASS

This section begins by describing the Jins Meme glasses we used to collect data. We then detail the data collection procedure we used for obtaining a pilot and full dataset of 10 gestures. Finally, we discuss the design of a machine learning classification pipeline to

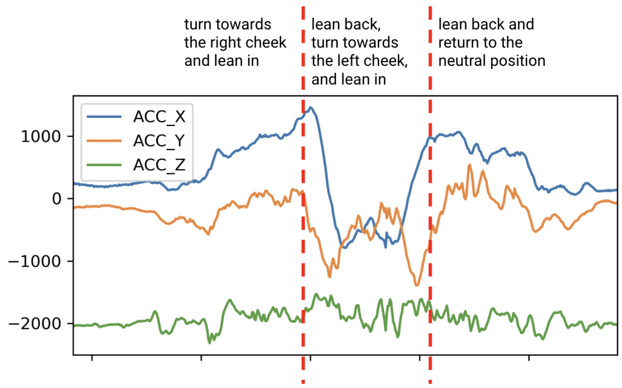

Figure 3: Example accelerometer signals from a participant performing 3 kisses starting on the right cheek.

recognize these gestures, and report both 10-fold cross validation and user independent accuracy scores.

3.1 System

For our studies, we used off-the-shelf Jins Meme glasses [1], which are equipped with three EOG electrodes in the nosepads, with the bridge of the nose acting as a reference electrode, leaving the left and right electrodes as active sensing channels as shown in Figure 2. In addition, the Jins Meme also includes a 6-axis IMU with a 3-axis gyroscope and a 3-axis accelerometer in the right leg of the glasses. The Jins Meme glasses transmit the sensor signals wirelessly through a Bluetooth Low Energy connection to a laptop which stores the streaming sensor data to disk. We hypothesized that the IMU would be able to capture the trajectory of the head movement while performing the kiss. We were also curious if the EOG electrodes would be able to detect the presence of another person that was not the wearer, and if patterns in changing presence could help recognize the gestures.

Given that the gestures had significant temporal information, we chose to perform our analysis using the k-nearest neighbors algorithm (kNN) with a dynamic time warp (DTW) as the distance metric. In this approach, we will have a database of examples (e.g. a training set) by which to compare the signal against (e.g. a test sample). The kNN algorithm considers training examples (e.g. a "template") one at a time, comparing it to the test example. For each comparison, the DTW metric is computed by first finding an alignment P mapping from each point in a training example X to each point in a testing example Y. Then the metric is returned as the Euclidean distance of the aligned training and test samples as shown in Equation 1.

$$DTW(X, Y) = \sqrt{\sum_{(i,j)\in P} \|X_i - Y_i\|^2} \quad (1)$$

This distance metric calculation also applies for multivariate signals, such as our sensor signals. The kNN algorithm then chooses the class that occurs the most frequently from the pool of k closest samples with the lowest distance (i.e. most similar). We used the Python library tslearn's implementation of the algorithm [26].

Table 1: Participant partner combinations during our study.

	Session 1		Session 2					
Participant	P1	P2	P3	P3	P4	P4	P5	P5
Partner	P2	P1	P4	P5	P3	P5	P3	P5

3.2 Data Collection Procedure

Participants formed pairings of all possible combinations within a data collection session. We ran two data collection sessions across two days with 2 participants (1 male, 1 female; average age = 24) and 3 participants (2 males, 1 female; average = 47), giving 2 and 5 pairing combinations, respectively, as described by Table 1. Within a pairing, one person acted as the participant and one person acted as the partner. The participant was asked to wear a pair of Jins Meme glasses, and the participant and partner pair was asked to perform the gestures listed in Table 2 together.

For the cheek-kiss gestures, participants were asked to touch cheeks, starting from a given side and alternating. For the nose-bump gesture, the participant touched his or her partner's nose with their own nose. In addition to performing the gestures, participants were asked to walk at a regular pace around the room for roughly half a minute. We included walking as a preliminary experiment for potentially being able to identify and segment kissing gestures from everyday activities. In total, each participant-partner combination performed each gesture 5 times, resulting in a dataset of 8 participant-partner combinations * 10 gestures * 5 of each gesture = 400 examples. Segmentation and gesture labels were manually annotated by listening to a microphone recording of the researcher facilitating the study instructing the participants.

4 ANALYSIS

For our preliminary work, we used simple machine learning techniques to gauge the feasibility of the kissing gestures using the sensing hardware available. After obtaining encouraging initial results from a pilot study performed on the first data collection session, we used sensor selections and hyperparameters findings to inform the full study, in which we analyzed the datasets from both sessions.

Table 2: Gestures performed by the participant and partner.

Duration	Body Part	Action	Parameters
4 reps	Cheek	Kiss	Start: left
4 reps	Cheek	Kiss	Start: right
3 reps	Cheek	Kiss	Start: left
3 reps	Cheek	Kiss	Start: right
2 reps	Cheek	Kiss	Start: left
2 reps	Cheek	Kiss	Start: right
1 rep	Cheek	Kiss	Start: left
1 rep	Cheek	Kiss	Start: right
1 rep	Nose	Bump	-
30 seconds	Legs	Walk	-

4.1 Pilot Study

We treated the first session of data collection as a pilot study for evaluating feasibility. We ran an initial experiment using standard 10-fold cross validation, and trained models on all of the sensor signals together, as well as each sensor independently (accelerometer, gyroscope, and EOG). These models used feature vectors of size 8, 3, 3, and 2, respectively. We trained and tested on entire segments as annotated by the researchers, and did not employ a sliding window which would be necessary for a real time system.

Across all of these experiments, we found that values of $k > 1$ for the kNN algorithm performed worse than when $k = 1$. Using all of the sensors combined, we obtained 61% accuracy on the 10 class classification problem (random chance baseline is 10%). Considering the accelerometer, gyroscope, and EOG sensors separately resulted in accuracies of 91%, 84%, and 23%, respectively. Encouraged by these early findings, we collected more data to evaluate our system in an user independent fashion.

4.2 Full Study

In our second session, we collected data from 3 more participants, resulting in 6 additional pairings. We combined this dataset with the data from the first session, and ran a similar evaluation, considering only the 3-axis accelerometer (which produced the best results in the pilot study). Using the the same 10-fold cross validation scheme as before, we obtained 83.0% accuracy.

We then tried leave-one-user-out cross validation. In this case, we select one participant as the test participant, and the model is trained on all of the remaining participants. The model is then evaluated on the test participant's data. Using the same analysis pipeline from the pilot study, but with the leave-one-user-out evaluation scheme, we obtained an accuracy of 74.33%.

5 DISCUSSION

While this paper describes the initial feasibility of recognizing a common greeting gesture, it remains to be seen how well our system works in more ecologically valid scenarios. One major shortcoming of our work was that none of the participants in either session of the user study came from a culture that performs such greetings. As a result, someone who grew up giving cheek kisses might perform them more quickly or more fluidly, giving different sensor signals. Collecting data from people that culturally perform this gesture would be a clear next step.

In addition to collecting more data, future work might include experimenting with more sophisticated algorithms as well. Although the DTW algorithm has seen reasonable amounts of success for time series classification, recent advances in support vector machines for time series (e.g., using a global alignment kernel) or deep neural networks might be able to produce better results. Furthermore, dedicated feature engineering (such as using autocorrelation for repetition counting) might help prevent confusion between gestures starting on the same side but with different repetitions.

In this work, we have specifically discussed the detection of a specific type of greeting. However, this gesture is limited primarily to Europe, Africa, and South America. Other parts of the world use different gestures for greeting. For instance, in China and Japan, bowing is the standard, while pressing the hands together is common in Thailand and India. In the United Kingdom and United States, handshakes are the norm for greeting someone. These additional gestures make for interesting future gesture recognition work with, for example, smart watches.

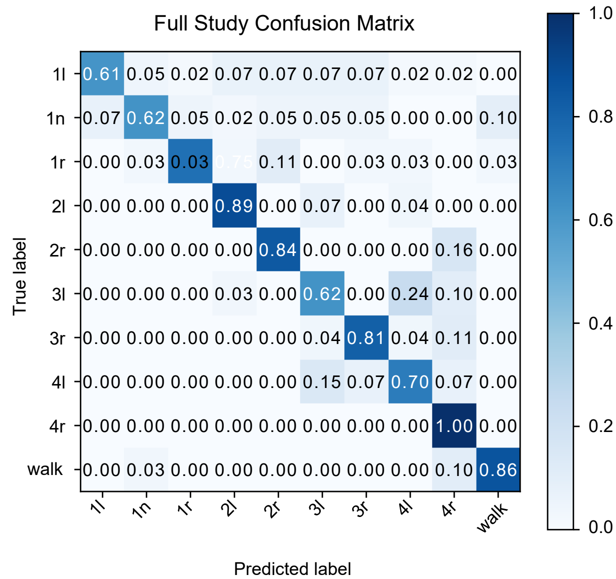

Figure 4: Confusion matrix depicting the results of evaluating the gesture classifier on a dataset of 5 participants. The gesture labels are of the syntax <num_kiss><which_side>. The letters to indicate which side the kisses start on are mapped as follows: l = left, r = right, n = nose. For example, 2r corresponds to 2 kisses, starting on the right cheek.

6 CONCLUSION

In this paper, we motivated the recognition of different kinds of cheek kisses as a technique for passive context sensing and awareness. We then discussed the collection of two datasets, comprising 5 participants in total performing 10 different gestures while wearing the Jins Meme glasses. Finally, we reported a 10-fold cross validation accuracy of 83.0% and a user independent accuracy of 74.33% when evaluating a kNN with DTW model using a leave-one-user-out schema. We conclude by discussing the limitations of our dataset as well as only recognizing one kind of greeting, and propose future work ideas given our encouraging results.

ACKNOWLEDGMENTS

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (MSIT) (No.2019-0-01270, WISE AR UI/UX Platform Development for Smartglasses).

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