Symbiotic Interfaces For Wearable Face Recognition

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Abstract

We introduce a wearable face detection method that exploits constraints in face scale and orientation imposed by the proximity of participants in near social interactions. Using this method we describe a wearable system that perceives "social engagement," i.e., when the wearer begins to interact with other individuals. One possible application is improving the interfaces of portable consumer electronics, such as cellular phones, to avoid interrupting the user during face-to-face interactions. Our experimental system proved $> 90\%$ accurate when tested on wearable video data captured at a professional conference. Over three hundred individuals were captured, and the data was separated into independent training and test sets. A goal is to incorporate user interface in mobile machine recognition systems to improve performance. The user may provide real-time feedback to the system or may subtly cue the system through typical daily activities, such as turning to face a speaker, as to when conditions for recognition are favorable.

1 Introduction

In casual social interaction, it is easy to forget the names and identities of those we meet. The consequences can range from the need to be reintroduced to the "opportunity cost" of a missed business contact. At organized social gatherings, such as professional conferences, name tags are used to assist attendees' memories. Recently, electronic name tags have been used to transfer, index, and remember contact information for attendees [Borovoy et al., 1996]. For everyday situations where convention-style name tags are inappropriate, a wearable face recognition system may provide face-name associations and aid in recall of prior interactions with the person standing in front of the wearable user [Farringdon and Oni, 2000, Starner et al., 1997, Brzezowski et al., 1996, Iordanoglou et al., 2000].

Currently, such systems are computationally complex and create a drain on the limited battery resources of a wearable computer. However, when a conversant is socially engaged with the user, a weak constraint may be exploited for face recognition. Specifically, search over scale and orientation may be limited to that typical of the near social interaction distances. Thus, we desire a lightweight system that can detect social engagement and indicate that face recognition is appropriate. Wearable computers must balance their interfaces against human burden. For example, if the wearable computer interrupts its user during a social interaction (e.g. to alert him to a wireless telephone call), the conversation may be disrupted by the intrusion. Detection of social engagement allows for blocking or delaying interruptions appropriately during a conversation.

To visually identify social engagement, we wish to use features endemic of that social process. Eye fixation, patterns of change in head orientation, social conversational distance, and change in visual spatial content may be relevant [Selker et al., 2001, Reeves, 1993, Hall, 1963]. For now, as we are uncertain which features are appropriate for recognition, we induce a set of behaviors to assist the computer. Specifically, the wearer aligns x's on an head-up display with the eyes of the subject to be recognized. As we learn more about the applicability of our method from our sample data set, we will extend our recognition algorithms to include non-induced behaviors.

While there are many face detection, localization, and recognition algorithms in the literature that were considered as potential solutions to our problem [Feraud et al., 2001, Rowley et al., 1998, Schneiderman and Kanade, 2000, Leung et al., 1995], our task is to recognize social engagement in context of human behavior and the environment. Face presence may be one of the most important features, but it is not the only feature useful for segmenting engagement. In examination of 10 standard face databases ($> 19,000$ images), we found that background contents had little variation. By comparison, scenes obtained from a body-worn camera in everyday life contained highly varied scene backgrounds. In addition to the presence of the face, we would like to exploit the movement of the face with respect to the wearer's camera. Given prior work on the visual modeling of human interaction [Oliver et al., 1998, Ivanov et al., 1999, Moore, 2000, Starner and Pentland, 1998, Starner et al., 1998, Nefian, 1999], we chose hidden Markov Models(HMMs) as the basis of our recognition system.

2 Engagement Dataset

We collected video data from a wearable camera at an academic conference, a setting representative of social interaction of the wearer and new acquaintances. The capture environment was highly unconstrained and ranged from direct sunlight to darkened conference hall. Approximately 300 subjects were captured one or more times over 10 hours. The images in Figure 1 are locations in the video annotated by the wearer to be faces. Our prototype wearable camera video capture system (see Figure 2) consists of: a color camera, an infrared(IR) sensitive black and white camera, a low-power IR illuminator, two digital video(DV) recorder decks, one video character generator, one audio tone generator, a Sony Glasstron head-up display, and four lithium ion camcorder batteries. Output from the cameras is recorded to DV. The HMD augments the user's view with two 'x' characters. The 'x' characters represent known locations for a subject's eyes to appear in the video feed. To capture face data, the wearer of the vest approaches a subject and aligns the person's eyes with the two 'x' characters. The video is then annotated by the user pressing a button which injects an audio tone into the DV stream at the location of the face data.

Figure 1: Representative data set

Figure 2: Marks for user alignment and face capture apparatus

3 Method

The video data was automatically extracted into 2 second partitions and divided into two classes using frames annotated by the wearer. The two classes were "engagement" and "other". As may be expected, the number of engagement gestures per hour of interaction was much smaller than the number of examples in the garbage class. Since the wearer lined up two x's with the eyes of a viewed subject, the presence of a face could safely be guaranteed to be framed by a 360x360 subregion of the 720x480 DV frame at the annotated locations in the video. Faces present at engagement were large with respect to the subregion. We first convert to greyscale, deinterlace, and correct non-squareness of the image pixels in the subregion. We downsampled the preprocessed region of video to 22x22 images using the linear heat equations to gaussian diffuse each level of the pyramid before subsampling to the next level. Each resulting frame/element in a 2-second gesture example is one 22x22 greyscale subregion (484 element vector). We model the face class

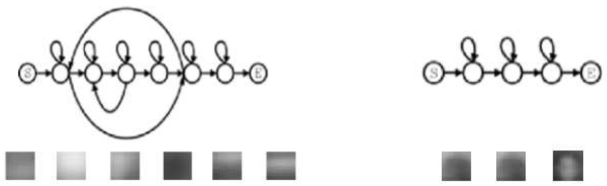

Figure 3: Other and Engagement classes

by a 3 state Left-Right HMM as shown in Figure 3. The other class was much more complex to model and required a 6 state ergodic model to capture the interplay of garbage types of scenes as shown in Figure 3. We plot the mean values of the state output probabilities. The presence of a face seems important for acceptance by the face model. The first state contains a rough face-like blob and is followed by a confused state that likely represents the alignment portion of our gesture. The final state is clearly face-like, with much sharper features than the first state and would be consistent with conversational engagement. Looking at the other class model, we see images that look like horizons and very dark or light scenes. The complexity of the model allowed wider variations in scene without loss in accuracy. Finally, background models could certainly be improved by building location aware models of environment specific features. represented.

4 Results and Evaluation Metrics

Table 1: Accuracy and confusion for engagement detection

experiment	*training set*	*independent test*
22x22 video stream	89.71%	90.10%

train confusion, N=843	*engagement*	*other*
engagement	82.1%(128)	17.9%(28)
other	8.6%(63)	91.3%(665)

test confusion, N=411	*engagement*	*other*
engagement	83.3%(50)	16.7%(10)
other	8.7%(30)	91.3%(314)

Accuracy results and confusion matrices are shown in Table 1. How effective is leveraging detection of social engagement as compared to continuously running face recognition? If we were to construct a wearable face recognition system using our engagement detector, we would combine the social engagement detector with a scale-tuned localizer and a face recognizer. The cost of the social engagement detector must be sufficiently small to allow for the larger costs of localization and recognition. This is described by the inequality

$$z - R_a * a \geq R_b * b$$

where $z := 1$ is the total resources available, a is the fixed cost of running engagement detection once in sec/frames, b is the fixed cost of running localization and recognition methods once in sec/frames, and R_a and R_b are the rate at which we can supply the respective detectors with frames in frames/sec, respectively.

However, R_b has a maximum value determined by either the fraction of false positives U_{fp} multiplied by the maximum input frame rate or the rate at which the user wants to be advised of the identity of a conversant R_{ui}. Thus,

$$R_b * b \geq max\{R_a * U_{fp}, R_{ui}\} * b$$

Note that fixating the camera on a true face could cause up to R_a frames per second to be delivered to the face recognizer. However, we assume that the user does not want to be updated this quickly or repeatedly (i.e. $R_{ui} << R_a$). We also assume that our rate of false positives will almost always be greater than the rate the user wants to be informed, leaving us with

$$1 - R_a * a \geq R_a * U_{fp} * b$$

For comparison purposes, we will assume that the average time per frame of processing for the localization and recognition process can be represented by some multiple of the average detection time (i.e. $b = c * a$). Thus, for a given multiplier c, we can determine the maximum rate of false positives allowable by the face detection process.

$$U_{fp} \leq \frac{1}{R_a * a * c} - \frac{1}{c}$$

Note that if $c \leq 1$, then the localization and recognition process runs faster than the face detection process. This situation would imply that performing face detection separately from face localization and recognition would not save processing time (i.e. localization and recognition should run continually - again, if real-time face recognition is the primary goal).Given a false positive rate U_{fp}, we solve the equation to determine the maximum allowable time for the localization and recognition process as compared to the detection process.Thus, we have a set of heuristics for determining when the separation of face detection and face localization and recognition is profitable.

$$c \leq \frac{1}{R_a * a * U_{fp}} - \frac{1}{U_{fp}}$$

5 Conclusion

Applying the metric from the previous section to our experimental results, we let $U_{fp} = .13$, $R_a = 30$, $a = \frac{1}{60}$ and solving for c we get $c \leq 7.69$. Thus any recognition method used may be up to 7.69 times slower than the engagement detection method and will have a limiting frame rate of about four frames per second. Given that our detection algorithm runs at 30fps, and our knowledge that principal component analysis based face recognition and alignment can run faster than roughly four times a second, we feel that engagement detection can be a successful foundation for wearable face recognition. Post-filtering outputs of detection may help eliminate false positives before recognition [Feraud et al., 2001]. Due to the face-like appearance of the final state of the HMM, it is likely that the output of our method could provide a reasonable first estimate of location to fine grain localization. Other cues including detection of head stillness, eye fixation, and conversational gestures like “hello, my name is ...” will likely reduce false positives[Reeves, 1993, Selker et al., 2001].

We described a platform built to capture video from a wearable user’s perspective and detailed a method for efficient engagement detection. We tested our system in a representative scenario and devised a metric for evaluating it’s efficacy as part of a face recognition scheme. In doing so, we demonstrated how the design of user interfaces that are aware of social contexts and constraints can positively affect recognition systems on the body. Finally, we have described how the detection of social engagement may be used, in its own right, to improve interfaces on portable consumer devices.

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