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# SRIM Scheme: An Impression-Management Scheme for Privacy-Aware Photo-Sharing Users

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A B S T R A C T

With the development of online social networks (OSNs) and modern smartphones, sharing photos with friends has become one of the most popular social activities. Since people usually prefer to give others a positive impression, impression management during photo sharing is becoming increasingly important. However, most of the existing privacy-aware solutions have two main drawbacks: ① Users must decide manually whether to share each photo with others or not, in order to build the desired impression; and ② users run a high risk of leaking sensitive relational information in group photos during photo sharing, such as their position as part of a couple, or their sexual identity. In this paper, we propose a social relation impression-management (SRIM) scheme to protect relational privacy and to automatically recommend an appropriate photo-sharing policy to users. To be more specific, we have designed a lightweight face-distance measurement that calculates the distances between users' faces within group photos by relying on photo metadata and face-detection results. These distances are then transformed into relations using proxemics. Furthermore, we propose a relation impression evaluation algorithm to evaluate and manage relational impressions. We developed a prototype and employed 21 volunteers to verify the functionalities of the SRIM scheme. The evaluation results show the effectiveness and efficiency of our proposed scheme.



## 1. Introduction

The rapid development of online social networks (OSNs) and mobile devices has accelerated the popularity of online photo-sharing platforms (PSPs). With camera-integrated smartphones, users can take photographs anywhere at any time, and then share them via PSPs such as WeChat, Facebook, or Flickr. They can also immediately (or at a later time) view photos published by friends or strangers, and comment on them.

However, shared photos may contain sensitive information that can be used to infer users' private information. In general, a shared photo always has three kinds of information [1]: content information (which can be used to infer "who," "what," etc.), profile information (i.e., metadata such as "when," "where," etc.), and relational information (i.e., implied relations between users, especially in group photos). For example, consider a typical scenario in which "Alice" falls in love with "Bob." Alice is excited and wants everyone to know about her feelings except for her parents. However, given the inseparability of photo content and the relevancy of implied relations, undesirable information may be exposed when Alice and her friends share photos with others. From this point of view, Alice should carefully consider group photos with Bob (even those that include other people) before posting them on PSPs. Otherwise, content, profile, and relational information about Alice may be revealed to undesirable users. In psychology, improving or maintaining the impression one gives to others is referred to as "impression management"; here, Alice is performing impression management by intentionally not revealing her relationship with Bob to her parents. Impression management includes avoiding major changes of impression when doing so is unnecessary, and is therefore affected by the issue of privacy leakage during photo sharing in PSPs.

Many studies have revealed the importance of impression management, and have summarized two main steps for achieving it: image recognition and policy recommendation. Many approaches have been proposed that focus on each separate step, such as image-recognition approaches [2–4] and access control approaches

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[1,5,6]. To the best of our knowledge, none of these studies have been able to address this problem in a user-friendly way. Besmer and Lipford [7] reported that concerns about photo policies were driven by "identity and impression-management" concerns rather than by fears about physical privacy, so they designed a tagged photo-management scheme to improve on the impression given to others by users. Klemperer et al. [8] also utilized photo tags to control user access in PSPs and to allow users to use keywords and captions to intuitively create and maintain access control policies. However, these schemes left the burden of sharing decisions to the users. Hoyle et al. [9] collected 14477 images from "lifeloggers" and conducted a survey on the reasons for not sharing these photos; "impression management" was found to be one of the three most important reasons. The common problem with existing work in this field is that such schemes seldom comprehensively consider the content, profile, and relational information—especially the sensitive information implied by the photos—before sharing them.

In this paper, we design a social relation impression-management (SRIM) scheme to improve users' relational impressions in PSPs. Our SRIM scheme not only prevents social relationships from being leaked, but also automatically recommends appropriate sharing policies for group photos. Based on photo metadata and face-detection results, we first design a lightweight face-distance measurement that calculates distances and transforms them into relations. We then propose a relation impression evaluation algorithm to evaluate and manage relational impressions. The major contributions of this paper are as follows:

- We propose a lightweight face-distance measurement method to quantify the distances between each pair of users appearing in group photos. Based on the theory of proxemics, we transform these face distances into relational strengths.
- We identify important factors that affect users' impressions, including face distances in group photos and trust coefficients of friends. Considering these factors, we design a relation impression evaluation algorithm to measure and manage relational impression.
- We develop an SRIM prototype to implement our idea. The evaluation results show that our algorithms can achieve our goals efficiently, and shed light on how the SRIM scheme enhances relational privacy and improves impressions.

The rest of the paper is organized as follows: Related work is introduced in Section 2, and Section 3 presents some preliminaries for this paper. We propose the face-distance measurement and relation impression evaluation algorithm in Section 4. Section 5 provides some evaluation results of our developed SRIM prototype. Finally, we conclude our work in Section 6.

## 2. Related work

With a huge number of photos being shared on PSPs, sensitive information implied by photos is being revealed, especially in group photos. Here, we review existing work associated with impression management in terms of two main steps: proxemics measurement [10–14], which measures the relationships between users in a photo; and policy recommendation [15–21], which recommends suitable policies to protect users' sensitive information.

### 2.1. Proxemics measurement

Most existing schemes attempt to solve proxemics problems in two ways. The first way is based on pose-detection technology. Yang and Ramanan [10] described a method for human pose estimation in static images based on a novel representation of part models. They found that co-occurrence and spatial relations are tree-structured, so relations can be efficiently captured. Based on this work, Yang et al. [11] further proposed image processes to build a social relation classification model using the features of poses, pictorial structures, and "touch code." They identified six specific touch codes, such as hand-hand, shoulder-shoulder, hand-shoulder, hand-elbow, elbow-shoulder, and hand-torso. They then used these poses to classify users' proxemics. The second way is based on position-prediction technology. Fathi et al. [12] presented a method for the detection and recognition of social interactions in a social event. They estimated and computed the line of sight for each face. They then detected and recognized the types of social interactions over time by using the roles and locations of individuals. Chakraborty et al. [13] tried to map people/face locations in two-dimensional (2D) images onto peoples' positions in three-dimensional (3D) spaces. They utilized spatial and structural features to predict the distances between users by using a support vector machine (SVM) classifier, whose accuracy reaches 76.4% for group photos. Unlike this previous work, we propose using a lightweight measurement to reduce calculation by using camera-imaging theory.

### 2.2. Policy recommendation

Squicciarini et al. [19] designed a recommendation system to help users make sharing polices. This system classifies photos using visual content and metadata, and then suggests policies for each category of photos, based on historical policies. Kairam et al. [20] designed a policy recommendation system that first considers the factor of esthetics. Combined with the factors of sharing behaviors and content features, this system can satisfy the requirements of respondents. Ni et al. [21] presented a large-scale empirical study on users' access control usage on Twitter and Instagram. The study revealed that sharing policy changing was affected by global events and festivals. According to this trend, they designed a recommendation system to automatically assign access control settings to users. However, these recommendation systems lose sight of relational information. In our work, we provide a solution to this problem by carefully combining proxemics measurement with impression management.

## 3. Preliminaries

In this section, we introduce some basic concepts that are adopted in this paper, and then present the motivation and basic idea of our scheme.

### 3.1. Basic concepts

In this section, we discuss two psychological concepts that are involved in photo sharing within social interaction: impression management and proxemics.

Impression management was first conceptualized by Erving Goffman in 1959 [22]; it is defined as "a conscious or subconscious process in which people attempt to influence the perceptions of other people about a person, object, or event." People perform impression management by regulating and controlling information within social interaction, such as by sharing group photos in OSNs. Here, we focus on providing an automatic or semiautomatic tool that allows users to control how others see their group photos. Since the relations depicted in group photos reflect users' real social relations to some extent, such implied relations can be used for impression management.

Proxemics is the study of the effects that population density has on behavior, communication, and social interaction. Hall [23] defined proxemics as "the interrelated observations and theories

**Table 1**
Interpersonal distance in proxemics.

| Interpersonal distance (phase) | Distance | Notes |
|---|---|---|
| Intimate close (I-C) | 15 cm or less | Reserved for close friends, lovers, children, and close family members |
| Intimate far (I-F) | 15–46 cm | |
| Personal close (P-C) | 46–76 cm | Used for conversations with friends, chatting with associates, and discussions in a group |
| Personal far (P-F) | 76–122 cm | |
| Social close (S-C) | 122–213 cm | Reserved for strangers, newly formed groups, and new acquaintances |
| Social far (S-F) | 213–366 cm | |
| Public close (Pu-C) | 366–762 cm | Used for speeches, lectures, and theater |
| Public far (Pu-F) | 762 cm or more | |

of man's use of space as a specialized elaboration of culture." We use the thresholds of interpersonal distance proposed in proxemics to identify relation types, as shown in Table 1.

### 3.2. Observations and basic idea

Our work is motivated by two observations in daily life. **Observation I:** Each person plays a different role in social networks, and is responsible for various social activities. For example, if there is no common interest between a child and his parents, then the relationship between the child and the parents is categorized as "partners"; however, when the child is with friends with common interests, their interaction can be treated as a social relationship. In general, people have different preferences for impression management in different social circles. Since even your best friend probably does not know everything about you, the level of intimacy is not enough to evaluate the relation between friends. **Observation II:** Social relations are an important part of social activities. They are something we all take for granted: Users continually cement the positive impressions of their social relations, and suppress the negative ones. Hoyle et al. [9] collected 14477 candid photos and obtained detailed sharing reasons regarding 1015 photos. According to that study, impression management is the most important factor affecting users' photo-sharing policies in OSNs. In impression management, it is common for two or more persons to co-occur in one photo. However, current PSPs, such as Facebook or WeChat, cannot provide mature tools for impression management. Although many studies about impression management have been performed [7,8,24,25], most focus only on direct information (e.g., on content [7,24] or profile [25] information). An impression-management tool for social relations is still urgently required.

To address the aforementioned problems, we propose an SRIM scheme to provide tools for users to manage their relational impressions and to effectively reduce the burden of decision-making in users' social networking activities. We have designed a policy recommendation framework that consists of a face-distance measurement method, proxemics, and relational impression evaluation. First, we calculate the actual physical distances between users' faces using face detection and photo metadata. Based on the theory of proxemics, we then use these distances to estimate the intimacy of relations. All shared group photos that friends receive help to form an impression of the user's social relation. If this impression changes dramatically, it indicates a possible deviation of the user's impression management (in this case, our scheme gives the user a warning). Otherwise, if a photo will smoothly enhance the desired relational impression of the user, it will be recommended for posting to a specific group.

## 4. The SRIM scheme

In this section, we introduce our SRIM scheme. Next, we propose face-distance measurements to calculate the distances between the users in group photos. We then propose a relation impression evaluation algorithm to manage relational impression. Finally, we discuss implementation issues.

### 4.1. System overview

Based on a user's historical sharing behaviors, our SRIM scheme offers recommendations and warnings; for example, it may recommend an appropriate group of recipients, or warn of inappropriate behavior. (Implementation details are provided in Section 4.4.) As shown in Fig. 1, when a new group photo is uploaded, faces are first detected and recognized. If there are more than two users in the photo, the distances between each pair of users are measured by face-distance measurement. Proxemics thresholds are then used to classify relation types. If a classification result has never appeared in someone's history, our scheme filters out these users in advance. In addition, we propose a relation impression evaluation algorithm to analyze each remaining user's historical relational impression and classify them into two groups (i.e., a group of recommended recipients and a group of non-recommended recipients). Finally, after the sharing decisions have been made, new distances in photos are used to update the historical records.

### 4.2. Face-distance measurement

Many methods have been proposed to measure social relations in group photos, including pose-based [11] and distance-based measurements [13]. In pose-based measurement, the pose and joint-occurring locations are qualitative analyses of users' relations. Changes in relations are difficult to quantify using this measurement, so it cannot be used to detect abnormal relation changes in our scheme. Existing distance-based measurement is a computation-consuming method that quantifies users' relations using machine learning and image-processing techniques. These methods are highly dependent on training data. In contrast to most existing measurement methods, our scheme uses a lightweight face-distance measurement to measure distances between users in group photos. The proposed method is based on the image principle of a camera and uses proxemics thresholds to identify users' relation types. It makes full use of several pieces of inside information from the camera, and possesses both high accuracy and a low computational overhead.

To provide face distances between users who are shown in the same photo, our scheme uses face detection and the 35 mm equivalent focal length from the photographs' exchangeable image file (EXIF) metadata. Most modern digital cameras change the focal length into a 35 mm equivalent focal length, and use 35 mm film to image digital photos instead of using a general charge-coupled device (CCD). Thus, it is easy to convert the distances between any two points in a photograph into the ratio of 35 mm film (36 mm wide and 24 mm high). When new users create accounts, they are required to upload one or more photos of their faces. Users are encouraged to provide the width values of their faces, since our

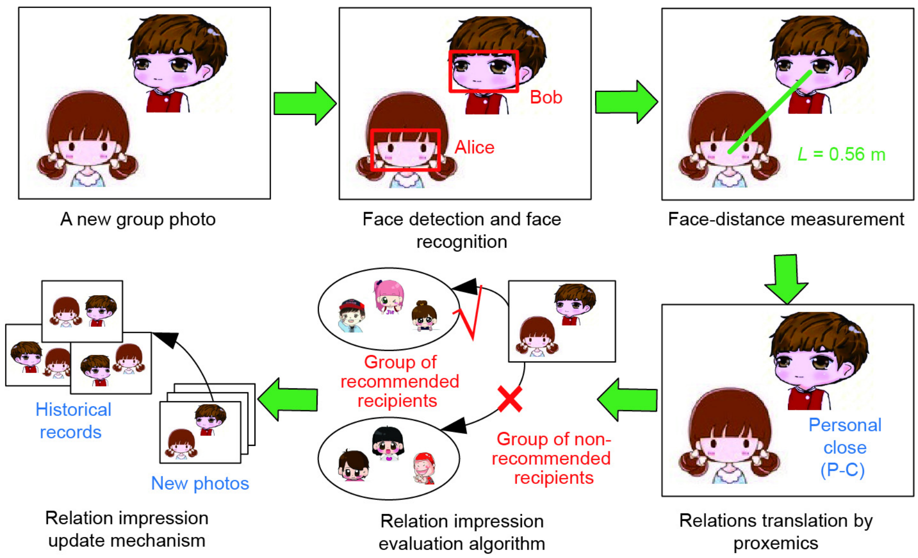


**Fig. 1.** Flow chart of our SRIM scheme. $L$: distance between two users' faces.

method is based on the width of the user's face. If users do not enter their face widths, we use a default value of 14 cm. (This default value still yields an acceptable result, as discussed in Section 5.1.)

Our method simplifies the imaging system of a typical camera, as shown in Fig. 2. The parameters $w_1$ and $w_2$ denote the physical face widths of user 1 and user 2, respectively. The parameters $l_1$ and $l_4$ denote the face widths of user 1 and user 2 in the photo, respectively. Parameter $l_2$ denotes the distance between the faces of user 1 and user 2 in the photo, and $l_3$ denotes the distance between the face of user 2 (the more remote one) in the photo and the central point of the photo. Parameter $f$ denotes the focal length of the camera. We can then obtain the distances from the camera to user 1 and user 2 respectively, which are denoted as $d_1 = fw_1/l_1$ and $d_2 = fw_2/l_4$. The distance between the two users' faces, $L$, is calculated as follows:

$$L = \sqrt{(d_2 - d_1)^2 + (h_1 + h_2 + h_3 + h_4)^2} \tag{1}$$

where $h_2$ is the face distance between user 1 and user 2′, and user 2′ is the photographic projection of user 2 onto a surface at distance $d_1$ from camera, such that the face distance can be denoted as $h_2 = l_2 d_1/f$; the difference between the photographic projection and the vertical positioning projection $h_3$ can be calculated as $h_3 = l_3(d_2 - d_1)/f$; and $h_1$ and $h_4$ are equal to half of the face width, which can be described as $h_1 = w_1/2$ and $h_4 = w_2/2$, respectively. Thus, Eq. (1) can be rewritten as follows:

$$L = \sqrt{\left(\frac{w_1}{l_1} - \frac{w_2}{l_4}\right)^2 \cdot f^2 + \left[\frac{w_1 + w_2}{2} + \frac{(l_2 - l_3)w_1}{l_1} + \frac{l_3 w_2}{l_4}\right]^2} \tag{2}$$

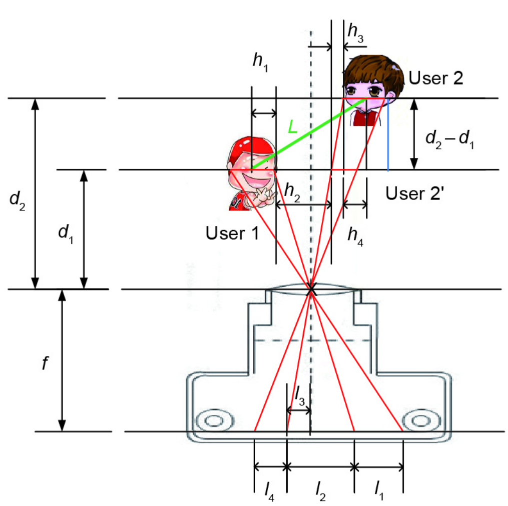


**Fig. 2.** Face-distance measurement.

### 4.3. The relation impression evaluation algorithm

We first introduce two basic phenomena of impression formation from real life. One phenomenon is that an impression is not formed based on the information from only one person. Inspired by this, our evaluation algorithms consider not only the shared photos posted by owners, but also the stakeholders (i.e., those who co-occur in the group photo in addition to the owners). The second phenomenon is that an impression is accumulated over time rather than being formed by just a few photos. Intuitively, if the relational impression in shared photos is sufficient and steady, a change in this impression is more likely to be evaluated by recipients.

For example, let us revisit the story about Alice and Bob. Carol is a teacher, and Alice wants to make a good impression on Carol. As shown in Fig. 3(a), different photo sets of Alice and Bob are shown in PSPs. We denote the photo set that Alice sends to Carol as $D_x$, the one Bob sends to Carol as $D_y$, and the one Bob sends to Alice as $D_z$. Fig. 3(b) depicts how Alice evaluates her impression in Carol's mind.

(1) Alice wants to give Carol a relational impression, which is formed by Alice's uploaded photos $D_x$.

(2) Carol's impression of the relationship between Alice and Bob is denoted as $i'$, and is formed by Alice's uploaded photos $D_x$ and Bob's public photos $D_y$.

(3) However, Alice is unaware of the photo set $D_y$, which Bob shows to Carol. She can only guess it by using the photo set $D_z$ that Bob shows to Alice.

In general, our model includes three roles: the owner (i.e., the person who owns the photo, e.g., Alice), the stakeholders (i.e., those who co-occur in the group photo, e.g., Bob), and the recipient (i.e., the person who receives the photo, e.g., Carol). We denote these

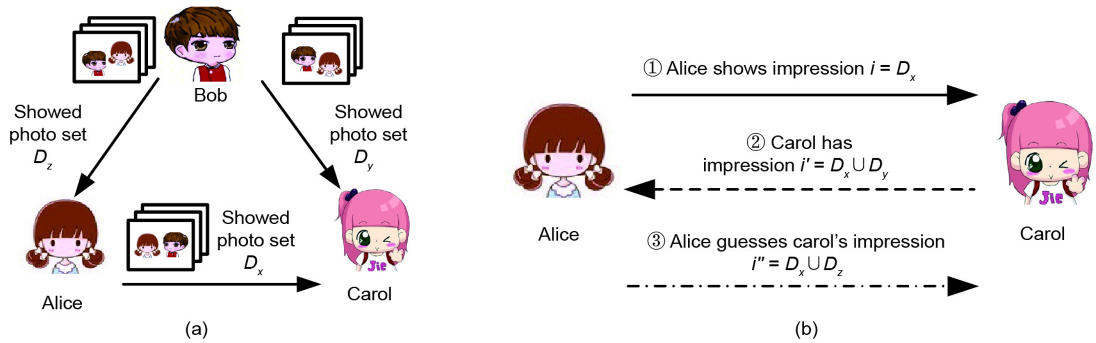


**Fig. 3.** A model of relational impression evaluation. (a) Showed photo sets; (b) guess model.

roles as users $o$, $s$, and $r$, respectively. We then define three kinds of impressions, as follows:

**Definition 1 (the owner's showed impression):** $f_o = \{1, 2, \ldots, m\}$ denotes the friend set of user $o$ in the group photos. Each recipient in the PSP has a relational impression set of user $o$'s friends, which is formed from the historical sharing records. The set is described as $I_o = \{i_{o,1}, i_{o,2}, \ldots, i_{o,m}\}$. To quantify the relations, we use historical profiles of face distances in order to initialize the relational impression of users, which is described as $I_o^{\text{init}} = \{D_{o,1}, D_{o,2}, \ldots, D_{o,m}\}$. Parameter $D_{o,1} = \{P_{\text{relation}_j} | j \in \{1, 2, \ldots, 8\}\}$ represents the distribution of distances in historical records, where $P_{\text{relation}_j}$ presents each probability of the eight relation types in proxemics. These distances are classified into eight relations, where the probability of each relation is presented as $P_{\text{relation}_j} = m_j/n$, $j = 1, 2, \ldots, 8$, in which parameter $m_j$ represents the number of relations $j$, and $n$ represents the number of total records.

The photo owners are not the only ones who provide information that results in recipients forming an impression; other stakeholders in the photos may post photos to the recipients if they are friends of the recipients.

**Definition 2 (the recipient's impression):** The real impression is defined as $I'_o = \{i'_{o,1}, i'_{o,2}, \ldots, i'_{o,m}\} = \{D'_{o,1}, D'_{o,2}, \ldots, D'_{o,m}\}$.

Since the owner cannot know the information that the stakeholders share with the recipient, the owner can only develop the optimum policies that lie within his or her access.

**Definition 3 (the owner's guessed impression):** The owner can guess the relational impression of the recipients; this guessed impression is defined as $I''_o = \{i''_{o,1}, i''_{o,2}, \ldots, i''_{o,m}\} = \{D''_{o,1}, D''_{o,2}, \ldots, D''_{o,m}\}$ .

Because our main idea is to evaluate a change in the relational impression from owner to recipient, we formulate our evaluation algorithm as follows: When a new photo is uploaded, we calculate the impact on all possible recipients. We denote the face distance between user $o$ and user $s$ as $L_{o,s}$. As soon as user $r$ receives a photo $\mu = \langle o, r, \langle o, s, L_{o,s} \rangle \rangle$ from user $o$, user $o$ can estimate the new impression that he or she believes c new impression, $i''^{\mu}_{o,s}$, is described as follows:

$$i''^{\mu}_{o,s} = t'_{o,s} \cdot D''^{\text{new}}_{o,s} + (1 - t'_{o,s}) \cdot i''^{\text{exist}}_{o,s} \tag{3}$$

where $i''^{\text{exist}}_{o,s}$ represents the existing impression, $D''^{\text{new}}_{o,s}$ is the new distribution of the shared photo set (i.e., with the new photo added and the oldest one deleted), and $t'_{o,s}$ represents the trust coefficient between user $o$ and user $r$. It is clear that the more similar $I'$ is to $I$, the more credible the impression from the owner is. However, $I'$ is unknown to user $o$, so $I''$ is used to calculate $t'_{o,s}$ approximately. Thus, $t'_{o,s}$ is calculated by the Hellinger distance, which is defined as follows:

$$t'_{o,s} = 1 - \frac{1}{2}\sqrt{\sum_{j=1}^{8}\left[\sqrt{i''_{o,s}(P_{\text{relation}_j})} - \sqrt{i_{o,s}(P_{\text{relation}_j})}\right]^2} \tag{4}$$

To simplify the complexity of the model, our model does not consider the forwarding effect on PSPs. When the evaluations are completed, the difference between two impressions can be decided as follows:

$$\text{Change} = 1 - \frac{1}{2}\sqrt{\sum_{j=1}^{8}\left[\sqrt{i''^{\mu}_{o,s}(P_{\text{relation}_j})} - \sqrt{i''^{\text{exist}}_{o,s}(P_{\text{relation}_j})}\right]^2} \tag{5}$$

$$\text{Result}_{o,s} = \begin{cases} \text{Recommend}, & \text{if change} < \text{threshold} \\ \text{Do not recommend}, & \text{otherwise} \end{cases} \tag{6}$$

In this paper, a threshold is used to adjust the recommendation range. We chose a lower threshold for sensitive recipients and a higher one for normal recipients.

**Multi-relation photos:** In general, the number of participants in a photo may affect the creation of a relational impression: The more participants appear in a photo, the less impression intensity the recipients feel. For example, given two group photos, A and B, and assuming that there are two participants in A and 20 participants in B, even if the users' relations are the same, a branding impression is much easier to apply for the two participants in A than for the 20 in B.

We assume that recipients will pay approximately equal attention to each group photo. Thus, one relation in a multi-relation photo (i.e., a photo with at least three users) will only receive a fraction of the recipient's attention. Each relation then occupies $2/[n_u(n_u - 1)]$ of the original size, where $n_u$ represents the number of users in the group photo.

However, recipients do not pay equal attention to each relation in a photograph, and a user in the photo who is closer to the camera will always receive more attention. Therefore, we measure the distance between each user and the camera, and use each pair of users to present the strength of their relation impression, as shown in Fig. 4. Thus, the weight of the relation of User a and User b can be denoted as follows:

$$\text{Weight}_{\text{a,b}} = \frac{2}{p} - \frac{d_\text{a} + d_\text{b}}{2\sum_{j=1}^{p} d_j} \tag{7}$$

where $p$ is the number of relations in the photograph.

The probability of each relation in a multi-relation photograph can be decided as follows:

$$P_{\text{relation}_j} = \frac{\sum_{k=1}^{m_j} \text{relation}_{j,k} \cdot \text{weight}_k}{\sum_{t=1}^{n} \text{relation}_t \cdot \text{weight}_t}, \quad j = 1, 2, \ldots, 8 \tag{8}$$

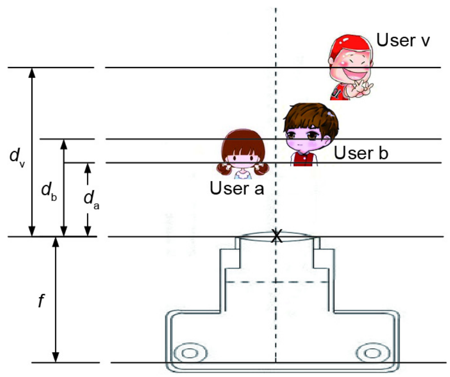


**Fig. 4.** Multi-relation measurement.

where $m_j$ is the assigned number of relation$_j$ and $n$ is the total record number.

As the number of users in the photo increases, the computational complexity will be unacceptable: The number of relations grows by $n_u$ factorial, where $n_u$ represents the number of users in the group photo. Fortunately, humans can only remember a limited number of things in a moment. For example, for photos showing gatherings or graduation ceremonies, recipients are only able to remember that someone is present as a member of the large group. Therefore, we design a threshold for the number of users in a photo: If there are seven or more people in the image, our SRIM scheme regards the image as a "big group" photo, and executes the preconfigured policies.

### *4.4. Implementation issues*

We have developed a prototype of the SRIM scheme that includes four specific technical details. The scheme depends on a MySQL database server, which is used to store the historical sharing records and relational impression information.

(1) **Face detection and recognition:** Functions in the SRIM scheme are implemented with the online application programming interface (API) service Face++.† The face-detection function of Face++ can locate the positions of faces and record the precise pixel coordinates for the face-distance measurement component. The other recognition functions can identify users in the group photos and provide a correlation between the users in group photos and users in PSPs. Moreover, in Ref. [26], the authors state that the identification rate in their Face++ approach is as high as 91.4%.

(2) **Face-distance measurement:** The biggest differences between our proposed measurement and the previous work [13] are the computational cost and accuracy. Although in Ref. [13], the authors were able to measure the face distance under less constraint, their method had a high computational cost and low accuracy (76.4% in group photos). This method is therefore difficult to use in practical applications such as relation evaluation because of its low accuracy, and difficult to use in mobile devices because of its high computational cost. However, in our face-distance measurement component, we extract the 35 mm equivalent focal length from the photos' EXIF metadata, which digital cameras such as single-lens reflex (SLR) cameras and mobile devices are equipped with. In this way, based on a knowledge of a camera's basic structure and working principle, we are able to measure the face distances with low error using Eq. (2).

(3) **Update mechanism:** We have designed a sliding window to select the most recent group photos (containing two or more users), in order to calculate changes of impression over time. In this study, we use the 50 most recent photos as the sliding window; this sliding window can be replaced by other numbers of photos or by other periods of time. When the historical records available are fewer than required, we use all the existing photos to calculate. In order to simulate a forgetting mechanism, when a new group photo is confirmed for sharing, the update mechanism pushes the oldest photo out of the sliding window and replaces it with the new one. By adjusting the parameter of the sliding window, users obtain a trend for their relational impression over time; this trend can be used to guide the development of an impression as desired by the user.

(4) **Threshold adjustment:** After all the recipients have been classified into two groups (i.e., the recommended group and the non-recommended group), a recommendation for sharing polices is generated. Owners provide feedback to the SRIM scheme by responding with either "satisfied" or "unsatisfied." When the owner's response is "satisfied," it indicates that the thresholds are correctly set at that time. When the classification is "unsatisfied," the thresholds of specific recipients should be adjusted independently. Our SRIM scheme will increase the thresholds of recipients who are moved from a recommended group to a non-recommended one by owners, and will decrease the thresholds of recipients in the opposite situation.

## 5. Performance evaluations

We simulated the PSP environment of Facebook by using the Stanford SNAP.‡ The Stanford SNAP contains 4039 nodes and 88 234 edges. We invited 21 volunteers to play the role of random nodes from the Facebook dataset in order to build a small, real-user dataset. As personal photos are difficult to collect, many existing schemes have been tested on datasets of this scale [1,27]. We also collected 1000 group photos from the 21 volunteers and their friends; the images from each respondent were taken over the long term using his or her smartphone.

### *5.1. Effectiveness of face-distance measurement*

Here, we evaluate the effectiveness of the face-distance measurement. Since the different relative angles of the connecting line between two users and the axis of the camera may affect detection, we conducted tests at different relative angles: 30°, 60°, 90°, 120°, and 150°. As shown in Fig. 5, we took photos from the relative angles of frontage and flank; these angles showed a significant difference in terms of visual effects.

In order to verify that our system is still effective when using default face widths, we used a default value (14 cm) to test our method. According to Table 2, the distance between users shows no obvious change at different relative angles, and most deviations are distributed within 5–10 cm. A possible influencing factor of the random deviations is the body movements when the users turn their faces. However, most of the face-distance measurement deviations in our experiment are less than 10 cm, which is acceptable for the measurement of relations in proxemics. In addition, the default value can be replaced by real face widths in order to achieve better results in the advanced version.

### *5.2. Evaluation of the SRIM scheme*

We collected our experimental data as follows. First, we investigated whether the volunteers (33 in total) were aware of the leakage risk of relational information in group photo sharing. Of

† http://www.faceplusplus.com.

‡ http://snap.stanford.edu/data.


**Fig. 5.** Visual effects of different relative angles. (a) Frontage position; (b) flank position.

**Table 2**
Test results of face-distance measurement (unit: m).

| True distance | 30° | | 60° | | 90° | | 120° | | 150° | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Distance | Deviation | Distance | Deviation | Distance | Deviation | Distance | Deviation | Distance | Deviation |
| 1.00 | 0.95 | 0.05 | 0.93 | 0.07 | 0.96 | 0.04 | 0.91 | 0.09 | 0.97 | 0.03 |
| 0.70 | 0.66 | 0.04 | 0.59 | 0.11 | 0.66 | 0.04 | 0.75 | −0.05 | 0.78 | −0.08 |
| 1.20 | 1.12 | 0.08 | 1.18 | 0.02 | 1.29 | −0.09 | 1.10 | 0.10 | 1.06 | 0.14 |

the 33 volunteers, 24 answered "yes," indicating that these people believe a risk exists when they appear with others in the same photo. Three of the 24 respondents also recognized that the distance between users in a photograph can be used to imply their relational strength. After the investigation, 21 volunteers were willing to provide group photos. We asked them to provide real-life group photos that had been chronologically shown to their friends.

To demonstrate the effectiveness and practicality of the SRIM scheme, we asked volunteers to play the roles of owners, stakeholders, and recipients in our simulation. We then extracted 13 groups of three roles (some volunteers played more than one role) to experience our SRIM. At the beginning, the procedure was explained in detail to the volunteers, as follows:

**Step 1:** Owners and stakeholders select 50 photos from their group photos, respectively, that establish an impression that they want to expose the recipients to.

**Step 2:** Stakeholders select a set of photos and display them to owners.

**Step 3:** Recipients choose 10 testing photos (including five photos that counter the impression and five normal photos) as the recipients' impression, $i'$ .

**Step 4:** We use the SRIM scheme to simultaneously calculate the impression in the testing photos and record the overhead of the system operation. The recommendation results are regarded as the owners' guessed impression, $i''$ .

**Step 5:** We compare $i''$ and $i'$ to evaluate the detection rates of our SRIM scheme.

### 5.2.1. Overhead

Compared with traditional OSNs, our proposed SRIM scheme adds two new modules: face-distance measurement and relation impression evaluation. We measured the overhead of these two parts independently (using a ThinkPad T430u laptop with Intel Core i7-3517U and 16G RAM). We selected 130 photos (10 testing photos of 13 groups) from Step 3, above, to process. As shown in Fig. 6, the face-distance measurement phase takes 0.0194 ms on average per photo, and the relation impression evaluation phase takes 0.0144 ms. According to previous work [28], it takes 330 ms per photo to complete face processing in Facebook, along with additional transmission time. The overheads of both added modules in our SRIM are negligible compared with those of traditional OSNs. For convenience, we sort the results by the overhead of the face-distance measurement in Fig. 6. Fig. 6 shows that the analysis of most testing photos does not exceed 0.03 ms. In addition, there are several spikes in relation impression evaluation, which result from relation computing in multi-relation photos. Fortunately, even in the worst cases, this does not affect system efficiency.

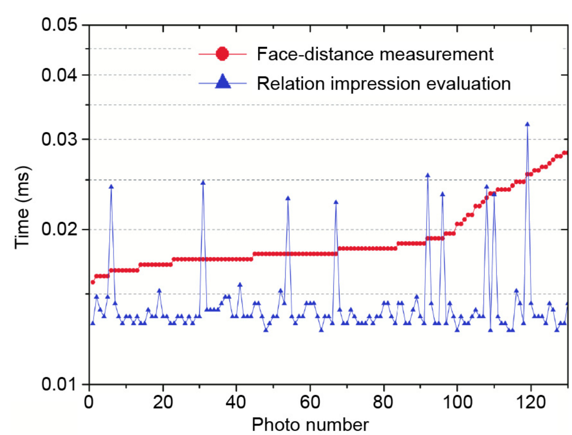


**Fig. 6.** The overhead of processing a photo.

### 5.2.2. Detection rates

Table 3 reports the results in terms of successful detection rates and reasons for mismatching. Out of a total of 130 testing photos,

**Table 3**
Detection rates of the SRIM scheme.

| Item types | | | Count | Proportion in the testing photos |
|---|---|---|---|---|
| Total training photos | | | 1000 | – |
| Total testing photos | | | 130 | – |
| Exactly matched photos | | | 108 | 83.08% |
| Mismatched photos | Error | False positive | 13 | 10.00% |
| | | False negative | 9 | 6.92% |
| | Mismatching reason | Huge differences from stakeholders | 14 | 10.77% |
| | | Poses and emotions | 6 | 4.62% |
| | | Other | 2 | 1.54% |

we achieved an overall accuracy of 83.08%. We found that there were a total of 22 mismatched photos. False positives accounted for about 59.09% of errors; in these cases, the owners set a higher restrictive threshold than usual. The mismatched photos resulting from the stakeholders accounted for 63.64% of the total errors, as the stakeholders showed entirely different photo sets to owners and recipients. The owners were unaware of the photos the stakeholders sent to recipients; however, they did their best with their limited background knowledge. Another common type of error was caused by the poses and emotions in the photos, which could impair the judgment of the recipients.

*5.2.3. Direct user evaluation*

In our experiment, many volunteers changed their minds, and decided against sharing some photos with the recipients that they had originally permitted sharing with. This finding demonstrates that users may not set a restrictive threshold for privacy settings for individual relations; thus, a system such as SRIM, which can accurately predict relational impressions, will provide an acceptable level of management for users. After the experiments, most volunteers expressed a keen interest in the project and an expectation of enjoying our SRIM scheme in future PSPs.

## 6. Conclusions

We have proposed an SRIM scheme to semi-automatically recommend a sharing policy regarding group photos, thus helping users to manage their social relation impressions on social activities in PSPs. The SRIM scheme first uses a lightweight face-distance measurement method, based on photo metadata and face-detection results, to effectively obtain the distances between users in group photos. It then translates the obtained distances into relations using proxemics thresholds. Next, we designed a novel relation impression evaluation algorithm by combining historical sharing records with the shared photos received by the photo owner and other possible stakeholders. Finally, we put forward a sharing strategy to the photo user, which included a group of recommended users to share the photo with, and a group of non-recommended users that would not be shared with. The simulation results showed the effectiveness and efficiency of our SRIM scheme. In our future work, we plan to add the factors of pose and expression in order to improve the precision of the relation impression evaluation.

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## Compliance with ethics guidelines

Fenghua Li, Zhe Sun, Ben Niu, Yunchuan Guo, and Ziwen Liu declare that they have no conflict of interest or financial conflicts to disclose.

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