Towards social pattern characterization in egocentric photo-streams

Maedeh Aghaei\textsuperscript{a,*}, Mariella Dimiccoli\textsuperscript{a,b}, Cristian Canton Ferrer\textsuperscript{c}, Petia Radeva\textsuperscript{a,b}

\textsuperscript{a}University of Barcelona, MAIA Department, Barcelona 08007, Spain
\textsuperscript{b}Computer Vision Center, Bellaterra (Cerdanyola) Barcelona 08193, Spain
\textsuperscript{c}Microsoft Research, Redmond, Washington 98052, United States

Abstract

Following the increasingly popular trend of social interaction analysis in egocentric vision, this manuscript proposes a new pipeline for automatic social pattern characterization of a wearable photo-camera user, relying on visual analysis of captured egocentric photos. The proposed framework consists of three major steps. The first step is dedicated to social interaction detection where the impact of several social signals is explored. Detected social events are inspected in the second step for categorization into different social meetings. These two steps act at event-level where each potential social event is modeled as a multi-dimensional time-series, whose dimensions correspond to a set of relevant features for each task, and LSTM is employed for time-series classification. The last step of the framework corresponds to the social pattern characterization of the user, where recurrences of the same person across the whole set of social events of the user are clustered to achieve a comprehensive understanding of the diversity and frequency of the social relations of the user. Experimental evaluation over a dataset acquired by a user wearing a photo-camera during a month demonstrates the relevance of the considered features for social interaction analysis, and show promising results on the task of social pattern characterization from egocentric photo-streams.

\textsuperscript{*}Corresponding author

Email address: aghaei.maya@gmail.com (Maedeh Aghaei)
1. Introduction

Automatic analysis of data collected by wearable cameras draws attention of the researchers in different topics in computer vision, ranging from object detection and recognition to event summarization and analysis in first-person vision [9, 10]. Among all these topics, social interaction analysis in particular has been an active topic of study [34, 5, 1, 3, 17, 45]. The motivation behind this interest is twofold. Firstly, the first-person paradigm offers the unique opportunity of revisiting the problem of social interaction detection and categorization from an unmediated source being the first-person, itself. Wearable cameras in comparison to the fixed surveillance cameras allow to capture natural photos of the daily interactions of the user, where the users naturally attempt to reach a clear view of the individuals who are engaged in a social interaction with them (see Fig. 1). Secondly, given the strong emotional impact of social interactions, their detection and categorization have a large potential for enabling novel applications in different fields, ranging from Entertainment to Preventive Medicine. For instance, in a particular scene recorded by a wearable camera, presence of social interactions is considered as an important factor to determine whether the event is likely to be viewed as worth keeping [45]. Also, in the context of memory recall of people affected by mild cognitive impairment, pictures of social interactions are specially suited to trigger autobiographical memory [43].

In sociology, the introduction of F-formation theory [29] was a foot-stone to
formalizing social interaction settings. F-formation is defined as a geometrical pattern that interacting people tend to follow by adjusting their location and orientation towards each other in the space to avoid mutual occlusion. The computer vision community later adopted the F-formation theory to detect groups of interacting people from images and videos [12, 18]. Early works about social interaction analysis in conventional images were motivated mainly by the video surveillance applications [38, 13]. Surveillance cameras however, capture the environment from a fixed and external perspective and fail in capturing real involvement in social interaction at personal level. For this purpose, wearable cameras are a suitable substitute for fixed cameras and offer the possibility of capturing social cues from a more intimate perspective, known as ego-vision or first-person vision. Nonetheless, social interaction analysis in ego-vision introduces new challenges in social signal processing in comparison to conventional third-person vision. Unpredictable motion of the camera leads to background clutter and abrupt lighting transitions. In addition, when the frame rate of the camera is low (2 fpsm in our case), further challenges such as complex visual appearance of natural scenes and drastic visual changes in even temporally adjacent photos make people tracking and their interaction analysis harder [1, 3].

In this paper, we build upon our previous work [3] going beyond social interaction analysis in egocentric photo-streams. The proposed pipeline suggests firstly, to study a wider set of features for social interaction detection and secondly, to categorize the detected social interactions into two broad categories of meetings. Following the proposed idea by Xiong et al. [44], we focus our attention on the meetings, as a special type of social interactions and its two broad formal and informal subcategories, since the importance of frequency of participation of an individual in any kind of these meetings is well recognized by the psychological and social scientists [32, 33, 41, 25]. Our hypothesis is that to detect and categorize social interactions, analysis of combination of environmental features and social signals transmitted by the visible people in the scene, as well as their evolution over time is required. Eventually, social pattern characterization of the user comes naturally as the result of discovery of recurring
people in the dataset and quantifying the frequency, the diversity and the type of the occurred social interactions with different individuals. Ideally, employing the entire proposed pipeline in this work, we would like to be able to answer questions such as *How often does the user engage in social interactions? With whom does the user interact most often? Are the interactions with this person mostly formal or informal? With how many people does the user interact during a month? How often does the user see a specific person?*

Social pattern characterization of individuals requires long time observation of their social interactions, and since wearable photo cameras allow long term recording of the life of a user, they are specifically suitable for this purpose. To demonstrate the generalization ability of the proposed approach, we employ our proposed model over a test set acquired by one user who wore the camera under free-living conditions over one month period while did not participate in acquiring the training set used for training the models. Possible applications of this comprehensive analysis are, for example, in medical and psychological studies aiming at investigating the feasibility of using a wearable camera for detecting relapse in people affected by depression [24] [8], for monitoring the lifestyle of stroke survivors [15], or in studies aiming at an ecological momentary...
assessment of social functioning in schizophrenia [20] for which is important to monitor the duration of social interactions. A visual overview of the proposed pipeline is given in Fig. 2. Social signals as well as environmental features are extracted for each frame and used to represent each sequence as a time-series. A LSTM is employed to classify each time-series, accordingly to the task at hand: social interaction detection or categorization. Face clustering on the other side enables determination of the diversity and the frequency of social interactions. Eventually, social pattern characterization comes naturally as the result of integration of all tasks. The contributions of this paper can be summarized as follows:

- Social interaction detection based on event-level analysis of different combination of a wide set of social signals.
- Social interaction categorization into formal or informal meetings, considering a new set of high-level image features.
- Social pattern characterization through the definition of the frequency and the diversity of social interactions of the user.
- Public release of an extensively-annotated egocentric dataset captured in a real-world setting consisting of 125,000 images acquired by 9 users.

The rest of the paper is organized as follows: Sec. 3 is devoted to social interaction detection. Sec. 4 details the proposed approach for social interaction categorization and Sec. 5 is dedicated to the social pattern characterization. Details about the dataset and experimental results are discussed in Sec. 6. Sec. 7 highlights the main conclusions and discusses the future work.

2. Related work

The importance of automatic analysis of visual data for the purposes of detection and categorization of social interactions has been recognized in several works by the computer vision community. Most of the previous works in social
interaction computing were focused on finding potential groups of interacting people, also known as Free-standing Conversational Groups (FCG) in conventional still images or videos. In this regard, Groh et al. [21] proposed to use the relative distance and shoulder orientations between each pair of people to measure social interactions on small temporal and spatial scales. This has been done through training a probabilistic classifier which can then be used for characterizing the social context. Cristani et al. [12] proposed to solve the task using a Hough-Voting F-Formation (HVFF) strategy to find the common area of interaction by accumulating the density of the overlapping votes of each interacting person. Built upon a multi-scale Hough-Voting policy, Setti et al. [37] modeled small FCG as well as large groups of people, relying on different voting sessions. The problem of finding F-formations has also been formulated as finding dominant sets and using proxemics by employing the graph clustering algorithm [27], graph-cuts framework for clustering individuals [38], heat-map based feature representation of interacting people [18], and defining an intermediate representation of how people interact [11].

The boom of interest in ego-vision during the past few years [10], naturally led to exploration of social interaction analysis in this setting where images and videos are captured by a camera which is typically worn on the chest or on the head of a user. Typically, the most exploited features in an egocentric scenario are the face location and pattern of attention of the visible individuals, along with the head movements of the first-person when the camera is worn on the head. Fathi et al. [17] proposed a Markov Random Field model to infer the 3D location to which a person is looking at during a social interaction, that relies on the camera intrinsic parameters. They further used this information to classify social interactions into three classes, namely discussion, dialogue and monologue, depending on the active role played by the participants in the interaction. To the best of our knowledge, this is the only previously introduced work about egocentric social interaction categorization. Later, Alletto et al. [5] proposed a method for identifying multiple social groups from egocentric videos, that do not rely on the camera intrinsic parameters for 3D projection; hence,
the method is applicable to any head-mounted wearable camera. Park et al. [40] introduced the concept of social saliency defined as the likelihood of joint attention from a spatial distribution of social members. A social formation is modeled as an electric dipole moment allowing to encode a spatial distribution of social members using a social formation feature. Recently, Yang et al. [45] proposed a procedure based on Hidden Markov Models to analyze social interaction sequences and detect them applying a Hidden Markov - Support Vector Machine (HM-SVM). Their focus was on modeling what they called interaction features, mainly physical information of head and body.

The common characteristics among all the above reviewed works are first, the high temporal resolution of videos (30-60 fps), which allows to rely on the temporal coherence among video frames to robustly estimate head pose of appearing people and modeling the foreground. Second, the head-mounted cameras allow the modeling of head movements and attention patterns of the user. And third, the pursued goal by them is basically restricted to find potential social groups of people in the scene, with exception of [17], that goes deeper into the categorization of social interactions, but strongly relies on head motion for that. The main limitation of high temporal resolution cameras is that they can acquire images for only relatively short periods of time (up to several hours) that makes them difficult to be used in order to detect patterns of social interactions.

The problem of social interaction analysis from egocentric photo-streams with low temporal resolution, overcomes the aforementioned limitation, but has received much less attention [1, 3, 4]. Since photo-cameras used to acquire photo-streams are typically used for long periods of time, they are commonly worn on the chest to make them more discrete. Consequently, important information about the user’s head movement is not available and attention estimation becomes unfeasible. In addition, in this particular setting, adjacent frames can present abrupt variations and introduce more difficulty along information processing. In the first attempt towards social interaction detection in egocentric photo-streams, Aghaei et al. [1] adapted the HVFF method to the egocentric setting, namely ego-HVFF, to predict social interactions among individuals with
the user at frame-level. This method inherently analyzes the social interactions in every frame of the video separately and eventually measures the probability of user social interaction of the user with each individual based on the ratio of the frames that the algorithm found them as interacting. Later, in another work [3], the authors proposed to model the temporal coherence of the social signals at sequence-level, by employing a special type of Recurrent Neural Networks (RNN) known as Long-Short Term Memory (LSTM). According to the F-formation notion, the studied social signals in both of these works are distance and orientation of the individuals with regards to the user. The authors reported that analysis of social signals at sequence-level leads to a better social interaction prediction accuracy. The authors also proposed a face clustering method [4], introducing a novel measure of similarity among faces, in conjunction with the results of social interaction detection and categorization, for social pattern characterization from egocentric photo-streams.

In this work, we propose a complete pipeline for social pattern characterization of a wearable photo-camera user, where for the first time the role of *facial expressions*, in combination with other conventional social signals is studied in social interaction analysis. The proposed model relies on the long term observation of social interactions of the user, where multiple high-level visual features aggregate together to achieve a more robust social interaction analysis. To the best of our knowledge, this work can be considered as the first comprehensive social pattern characterization study in egocentric vision.

### 3. Social interaction detection

We, as humans are naturally able to recognize if two or more people are interacting even only by looking at a sequences of images (see Fig. 3). However, this is not as trivial for a computer program. In this work, for social interaction detection task, we build upon our previous work by introducing additional features and study their effectiveness in improvement of the results. Specifically, given a *sequence*, a potential social segment of a photo-stream extracted by ap-
Figure 3: Examples of two sub-sampled sequences in our dataset. In (a) the user is involved in a social interaction while (b) demonstrates a sequence where although the user is among the crowd, but is not specifically interacting.

plying the video segmentation method [16], social signals are first extracted at frame-level, and later their evolution in terms of social signals is analyzed over time at sequence-level to detect social interactions.

3.1. Social signal extraction at frame-level

Tracking the appearance of people along time is generally considered as the first step prior to any social behavior analysis in machine vision. To track the appearing people in each sequence, we employ the extended-Bag-of-Tracklets (eBoT) [2] which is a multi-person tracking algorithm in egocentric photo-stream setting. The set of bounding boxes corresponding to the same face in a sequence, resulting from eBoT, is called a prototype, where the number of prototypes in a sequence is equal to the number of tracked people in it as more than one individual may appear in a single sequence.

In this work, as well as our previous work, we rely on the F-formation formalization for social interaction detection in the domain of egocentric photo-streams. As the F-formation model assumes a bird-view of the scene, we represent each bounding box in a prototype by a \((x, d, o)\) triplet, so that \(x\) denotes the position of the person in the horizontal axis of the image and with regards to the user, \(d\) denotes its distance, and \(o\) its head orientation. The tracking
process, directly provides us with the $x$ position of a face. However, in our egocentric setting, $x$ is not a reliable feature to be considered as it constantly goes under large variations due to the unpredictable movements of the camera and its low frame rate (see Fig. 3a). Moreover, when it comes to interaction with the user, the $x$ position of the visible people as far as they do not occlude each other, does not play a crucial role. Therefore, we only consider the $(d, o)$ pair to analyze the F-formation. Both parameters, $d$ and $o$ should be calculated for all the participants in the social interaction, being the user and the visible people in a sequence.

**Distance:** In the egocentric setting, the user is obviously located at no distance from the camera $O$ and the distance of the $j$-th tracked person $p_j$ in the scene from the camera, $d(O, p_j)$, is estimated based on the camera-pinhole model through learning its relation with the vertical face height of the person $[5]$. According to our observations, the relation between the face height of individuals and their distance from the camera is best modeled as a second degree polynomial of the face height of the person $[1]$

The data for training the polynomial regression function is obtained from a dataset that does not belong to the training and test datasets for the social interaction detection. For the fit, we used the height of the face of 3 different individuals measured in all the following set of distances $\{30, 50, 70, 100, 150, 200, 250\}$ cm.

The distance feature is represented by:

$$\varphi_d(p_j) = d(O, p_j) \in \mathcal{R}.$$  

Without loss of generality, in the feature vector we will omit the reference to the person $p_j$ and the wearable camera $O$.

**Orientation:** The head orientation of each individual gives a rough estimation of where the person is looking at. In this work, in addition to the commonly studied yaw ($\omega_z$) head orientation for social interaction detection, pitch ($\omega_y$) and roll ($\omega_x$) head orientation of all the visible faces are also extracted. Hence, the orientation feature is given by:

$$\varphi_o(p_j) = (\omega_x(p_j), \omega_y(p_j), \omega_z(p_j)) \in \mathcal{R}^3.$$
where each of \( \omega_x, \omega_y, \) and \( \omega_z \) has a value between \([-90^\circ, 90^\circ]\). As the camera is basically worn on the chest of the user, we only assume the user can possibly look at anywhere in the space, but with higher probability of looking at other engaged people in the interaction.

**Facial expression:** During a social interaction, people exhibit a large number of non-verbal communication cues including facial expressions. Facial expressions are often referred to as automatic demonstrations of affective internal states used as communicative means in interaction with others [22]. In crowded places, people often stand in close proximity to strangers with whom they do not necessarily interact. In this situation, relying solely on distance and orientation of the individuals for social interaction detection may lead to disputable predictions (see Fig. 4). Our observation on real social conditions led us to intuitively explore the role of facial expression as an additional feature beside the pure geometrical features imposed by the F-formation in social interaction detection.

In this work, facial expressions and face orientation are extracted by making use of Microsoft Cognitive Service\(^1\). Facial expression is presented as a predicted vector of probabilities for each of 8 different facial expressions consistently associated to emotions in the occidental culture, being *neutral, happiness, surprise, sadness, anger, disgust, fear,* and *contempt* [7]. For a given person \( p_j \), we proposed to consider the index of the dominant facial expression that is a discrete value between 1 (*neutral*) and 8 (*contempt*):

\[
\varphi_e(p_j) = \arg \max_{k\in 1,\ldots,8} e_k(p_j).
\]

### 3.2. Temporal representation of social signals

In this work, the problem of social interaction detection is formulated as a binary time-series classification, where the time-series dimensions correspond to the number of selected social signals for the analysis as explained in Sec.

\(^{1}\text{https://azure.microsoft.com/en-us/services/cognitive-services/face/}\)
Having the goal to detect social interactions of each tracked individual in a sequence with the user, as the complete setting, a 5-dimensional time-series representing the time-evolution of the k-th interaction features, over time is extracted for each prototype, separately. The task is to classify each time-series as interacting with the user or not. All the aforementioned interaction features, are extracted in every frame of the sequence at time step $\tau$ separately to build the time-series representation of a prototype:

$$\varphi_{detection}(\tau,p_j) = (\varphi_d(\tau,p_j),\varphi_o(\tau,p_j),\varphi_e(\tau,p_j)) \in \mathbb{R}^5, \quad \tau = 1,2,\ldots$$

3.3. Time-series classification by LSTM

Time-series classification is a predictive modeling problem and what makes this problem difficult is that the original sequences can vary in length, be comprised of a very large vocabulary of input symbols and may require the model to learn the long-term context or dependencies between symbols in the input time-series. In this context, RNNs by considering the notion of order in time thanks to their embedded feedback loop, showed great promise to grasp the
information hidden among steps of a sequence. The combination of backpropagation in conjunction with an optimization method such as gradient descent is a common method of training of RNNs. Back Propagation Through Time (BPTT) is considered as an extension of the backpropagation used for training of RNNs, in which a time element is added which extends the series of functions for which it calculates derivatives with the chain rule. In this work, a variation of RNNs, namely LSTM [23] is used for the classification task which thanks to its embedded memory cells is also able to control how information flows through the network and in this way it overcomes the exponential error decay problem of the RNNs. The effectiveness of the LSTM is demonstrated in previous approaches ranging from activity and object detection [31], recognition and segmentation to image and video captioning [28].

Being $\zeta$ the memory cell, at time step $\tau$, $\zeta$’s output $y^\zeta(\tau)$ is computed as:

$$y^\zeta(\tau) = y^{out}(\tau)h(S^\zeta(\tau)),$$

where $S^\zeta(\tau)$ is the internal state of the LSTM, also known as the heart of the memory cell, $h$ is a differentiable function that scales memory cell outputs computed from the internal state $S^\zeta$ and $y^{out}(\tau)$ is the output of the output gate. The internal state $S^\zeta$ has a self-connected recurrent edge with fixed unit weight with linear activation. Because this edge spans adjacent time steps with constant weight, error can flow across time steps without vanishing or exploding. The internal state $S^\zeta(\tau)$ is computed as:

$$\begin{cases} S^\zeta(0) = 0, \tau = 0 \\ S^\zeta(\tau) = S^\zeta(\tau - 1)y^{forget}(\tau) + y^{in}(\tau)g(net^\zeta(\tau)), \tau > 0 \end{cases}$$

being $y^{in}$ and $y^{forget}$ functions of the parameters ($\varphi_{\text{detection}}$, in our case) and outputs of the cell’s input gate, and forget gate, respectively. $net^\zeta$ is the combination of present input and past cell state which gets fed not only to the cell itself, but also to each of its three gates. $g$ is a differentiable function that squashes $net^\zeta$. We refer the reader to [23] for a more detailed description of
Figure 5: Example of two sub-sampled sequences, demonstrating the engagement of the user in different categories of social interactions; a formal meeting (a), and an informal meeting (b).

4. Social interaction categorization

Social interaction categorization is the task of characterizing type of a social interaction. In the literature, three major elements have been typically exploited for social interaction categorization: the physical setting or place, the social environment, and the activities surrounding the interaction [35]. In this work, following Xiong et al. [44] we propose to categorize social interactions into two broad categories of common social interactions as formal meetings and informal meetings, also known as informal gatherings.

Meetings are defined as gatherings at which humans communicate, convince, cajole, conspire, and collaborate [44]. In general sociology, a formal meeting is defined as a pre-planned event where two or more people come together at a pre-planned place at a particular time to discuss specific matters for the purposes of achieving a specific goal [14]. An informal meeting is more casual, and less planning is involved and usually can take place anywhere, such as a restaurant or a park. Looking closely at the definition of formal and informal meetings from a computer vision perspective, environmental features show sign...
of discriminative power in their categorization. Therefore, we base our approach for social interaction categorization on the use of environmental features. In addition to them, we also attempt to study the impact of the facial expressions of individuals on characterizing the category of a social interaction. Our approach takes into account the temporal evolution of both environmental and facial expression features by modeling them as multi-dimensional time-series, and relies on the classification power of LSTM for binary classification of each time-series into either a formal or an informal meeting.

4.1. Feature extraction

Global features: As explained earlier in this section, the surrounding environment of an interaction is considered among the main indicators for categorizing a meeting. Among different features for image representation, global features learned by CNN, known as CNN features showed exceptional results for global representation of the context in images [19]. Each component of the CNN feature vector has some semantic content and corresponds to a virtual concept word which enables to encode the high-level semantic meanings of an image into a high-dimensional vector. In this work, we represent each image with a feature vector extracted by taking the output of the last fully connected layer of the VGGNet (VGG16) [39] pre-trained on the Imagenet dataset [14]. However, since the image feature vector consists of thousands of variables (4096 in our case), the computational cost is not negligible when it comes to further processing. In addition, the Hughes phenomenon [26] is inevitable when it comes to learn a high-dimensional feature space with limited number of training samples in machine learning in general and in RNNs, specifically [36]. In this regard, several works have been proposed previously to resolve the curse of dimensionality of CNN features.

We propose to re-write the CNN features as discrete words [6]. Our approach takes advantage of the inverted-index approach to deal with the sparsity of the CNN features to associate each component of the feature vector with a unique alphanumeric keyword. This leads to a textual representation of the
CNN features in which the relative term is proportionally related to the feature intensity. This method showed great promises in retrieval applications. In this work, the proposed idea by Amato et al. is adapted to our problem for feature dimensionality reduction.

Let us represent each component of the L2-normalized CNN feature vector, $f_k, k = 1, \ldots, 4096$ as a word:

$$w_k = \lfloor Qf_k \rfloor,$$

where $\lfloor \rfloor$ denotes the floor function, and $Q$ is an integer positive quantification factor being $Q > 1$. For instance, if we fix $Q = 2$, for $f_k < 0.5$, then $w_k = 0$, while for $f_k \geq 0.5$, $w_k = 1$. The factor $Q$ has a regulator effect on the features for further processing. The smaller the $Q$ the sparser is the new feature vector and it represents less details about the original feature vector. In this work, $Q = 15$ is used which results in highly sparse feature representation. As a result, we obtain a feature vector of integer values: $(w_1, w_2, \ldots, w_{4096})$.

Given that the obtained word representation is very sparse, a PCA is applied over the so obtained feature vectors extracted from all the images of the dataset and from the emerging representation, 95% of the most important information are kept. This process results in a 35-dimensional feature vector, $\varphi_{CNN} \in \mathbb{R}^{35}$, while keeping the most important environmental features of the image.
**Facial expression:** Following our hypothesis that formal and informal meetings can be characterized by the environmental characteristic as well as the facial expression of participants, integration of information regarding facial expression in our model is required. A proof for this hypothesis is illustrated on Fig. 6 that shows the bar-plot of eight facial expressions for both formal and informal meetings. These bar-plots, obtained using ground truth information, suggest that people express more freely their emotions in informal meetings. Facial expression features in this task are extracted as the mean of facial expressions of the total number of $J$ people detected in each frame of a sequence:

$$\varphi_{c,k} = \frac{1}{J} \sum_{j=1}^{J} e_k(p_j), k = 1, \ldots, 8.$$ 

### 4.2. Temporal analysis of representative features

To achieve joint effect of global image and people facial expression features on social interaction categorization, the 8-dimensional vector of facial expression probabilities ($\varphi_{c}(\tau)$) is directly concatenated to the environmental features represented by global image characteristics of the event ($\varphi_{CNN}(\tau)$). Given a sequence, the time-series of interaction sequences are constructed as follows for the social interaction categorization:

$$\varphi(\tau) = (\varphi_{CNN}(\tau), \varphi_{c}(\tau)) \in \mathbb{R}^{43}, \tau = 1, 2, \ldots$$

Further, time-series classification task into either a formal or an informal meeting is reached relying on the LSTM power for time-series classification.

### 5. Social pattern characterization

#### 5.1. Generic social interaction characterization

Characterizing the social pattern of an individual, implies the ability of defining the nature of social interactions of the user from various temporal (how often, how long, etc.) and social (with how many people, individual or group interaction, who are the most frequent people, what is the interaction...
type, etc.) aspects. Providing a definition within the aforementioned contexts, demands social interaction analysis of the user across several events during a long period of time. For this purpose, we define four concepts to estimate social interactions, namely *frequency, social trend, diversity, and duration*.

**Definition:** *Frequency* is defined as the rate of formal (informal) interactions of a person normalized by the total number of interactions:

\[ F_{\text{formal(informal)}} = \#\text{formal(informal) interactions}/\#\text{days} \]

**Definition:** *Social trend* indicates whether the majority of social interactions of a person are formal (informal), respectively:

\[ A_{\text{formal(informal)}} = \#\text{formal(informal) interactions}/\#\text{all interactions} \]

**Definition:** *Diversity* demonstrates how diverse are social interactions of a person. The term is defined as the exponential of the Shannon entropy calculated with natural logarithms, namely:

\[ D = 1/2 \exp \left( - \sum_{i \in \{\text{formal, informal}\}} A_i \ln(A_i) \right) \]

Note that when the person has the same number of formal and informal interactions (i.e. \( A_{\text{formal}} = A_{\text{informal}} = 0.5 \)), \( D = 1 \).

**Definition:** *Duration* is the longitude of a social interaction, it is defined as \( L(i) \) for each social interaction \( i \) of the user, it is proportional to the longitude of the sequence corresponding to that social interaction, say \( L(i) = T(i)r \), where \( T(i) \) is the number of frames of \( i \)-th interaction and \( r \) is the frame rate of the camera. Different statistics can be applied on the duration of interactions like mean, median or standard deviation in order to characterize social interactions and extract the social pattern.

### 5.2. Person-specific social interaction characterization

In this subsection, we consider the concepts for social interaction characterization of the user within the context of interaction with a specific person,
with the goal of going deeper into the characterization of the social relations of the user. For this purpose, firstly all the interactions of the user with a certain person need to be localized. To this goal, a face clustering method adapted for egocentric photo-streams [4] is employed, which essentially achieves the desired goal through discovery of various appearances of the same person among all the social events of the user. The face clustering method is applied on the results of the social interaction detection step. To cope with the extreme intra-class variability of faces, it builds upon the multi-face tracking outcome. In a single event, tracking gathers a set of different appearances of the same face in that event, called a face-set in this context, which allows to reshape the face clustering task in different events to face-set clustering.

The deterministic factor in deciding whether two different face-sets belong to the same cluster i.e. represent the same person, is defined through a dissimilarity measure. Let $R$ and $T$ be a reference and a target face-sets, respectively. Let us assume $S^R$ is the similarity matrix between all possible pairs of face-examples in $R$, and $S^T$ is the similarity matrix between face-examples in $R$ and face-examples in $T$. The dissimilarity between $T$ and $R$, $\delta(R, T)$, is calculated as the absolute difference between the median value $\mu$ of $S^R$ and $S^T$, respectively:

$$\delta(R, T) = |\mu^R - \mu^T|.$$ 

A hierarchical clustering technique is applied to group the face-sets according to their pair-wise dissimilarity value. The cut-off threshold for the agglomerative clustering is chosen empirically over a separate learning dataset and corresponds to the median value of all dissimilarities between the face-sets corresponding to the same person. Fig. 7 shows a few images in one resulting cluster obtained
together with an index to which sequence each element of the cluster belongs.
One can appreciate the visual variance of the faces in a cluster.

5.3. Face-cluster analysis

Our final goal in this work is to characterize the social pattern of a user from egocentric images taken for a long period (e.g. a month). Let $C = \{c_j\}$, $j = 1, \ldots, J$ be the set of clusters obtained by applying the face-set clustering method on the detected interacting prototypes, where $J$ ideally corresponds to the total number of people who appeared in all social events of the user. Each cluster, $c_j$, ideally contains all the different appearances of the person $p_j$ across different social events, and $|c_j|$ is the cardinality of $c_j$ which demonstrates the number of social interactions events of the user with the person $p_j$ during the observation period.

As the employed clustering method as well as the proposed method for social interaction detection and categorization act at sequence-level, inferring the interaction state of each sequence inside a cluster is straightforward. The frequency, the social trend, the diversity and the duration of the interactions with a specific person, can be computed, 5.1, by restricting the interactions considered to the ones with the person of interest.

6. Experiments and discussion

In this section, we introduce our dataset for social pattern characterization in egocentric photo-streams, namely EgoSocialStyle and describe the proposed experimental setup to validate our proposed approach. A comprehensive discussion to provide broader insight over the obtained results is also given in this section.

6.1. Experimental setting

6.1.1. Data

To the best of our knowledge, this work is the first attempt to characterize automatically the social pattern of a person relying exclusively on visual data.
Lack of previous studies goes with the lack of the public dataset on this considered purpose, which led us to build a new dataset to validate jointly all the tasks of our proposed method. Our dataset has been acquired by 9 users wearing a Narrative clip camera during the participation in gathering the dataset while they were living their daily life without any constrains. The camera was set to automatically capture a photo every 30 seconds once being worn. The participants who gathered the dataset had different ages and profiles and wore the camera in different and random days and times of the week. Sequences in our dataset have different lengths, varying from 20 to 60 frames (10 to 30 minutes of interactions).

The training set of EgoSocialStyle is an extended version of the dataset previously introduced in [3]. It has been acquired by 8 users; each user wore the camera for a number of non-consecutive days over a total of 100 days period, collecting over 100,000 images in total, where in 3,000 images among them a total number of 62 different persons appear.

The test set is acquired by a single user, who did not participate in acquiring the training set as we aimed to study the generalization ability of our model for social pattern characterization of a person. The user wore the camera for 30 consecutive days collecting 25,200 images, where 2,639 of which correspond to social events. There are 35 sequences with more than one person appearing in them over 113, in total. 40 different trackable persons appear in the test set.

Face annotations in the whole dataset are attained using the Microsoft face annotation tool [7]. Participants were asked to provide a label (interacting/not interacting, formal/informal) for their own sequences. Table 1 provides further details of the proposed dataset.

6.1.2. Data augmentation

Large amount of data for better training of deep models is a well recognized necessity. However, the required time to acquire and label real data for this purpose is not negligible and is where artificial data augmentation could have an impact. A proper data augmentation is one which provides a reasonable
Table 1: EgoSocialStyle dataset

|     | Users | Days | Images | Social Images | People | Sequences | Prototypes | Interacting | Formal |
|-----|-------|------|--------|---------------|--------|-----------|------------|-------------|--------|
| Train | 8     | 100  | 100,000| 3,000         | 62     | 106       | 132        | 102         | 42     |
| Test  | 1     | 30   | 25,200 | 2,639         | 40     | 113       | 172        | 130         | 25     |

set of data in addition and similar to the already existing data in the training set, but also slightly different from them to reduce overfitting of the model in learning a task \[42\]. Besides the impact of data augmentation in the production of additional data, it is also considered a helpful tool to provide balance to unbalanced data. This specially is of interest in our case where to acquire sequences without any social interaction it is more difficult than sequences with social interaction.

To augment the data at hand, we employed the proposed idea by Krizhevsky et al. \[30\]. The principle idea consists of augmenting signals by adding slight variations to them, which can be done by adding eigen-features on top of each different feature in a sequence. This has been achieved through applying PCA and then adding multiples of the found principal components to each sequence, with magnitudes proportional to the corresponding eigenvalues times a random variable drawn from a Gaussian with mean zero and small standard deviation (0.01, in this work). This scheme generates more data in addition to the original training data by applying label-preserving transformations to them.

Let $\Phi = (\varphi_{1,n}(\tau), \varphi_{2,n}(\tau), \ldots, \varphi_{K,n}(\tau))$, $n = 1, \ldots, N$ is the set of all the $N$ time series in our training set where $\tau = 1, \ldots, T$, is the length of the sequences and consequently the time-series and, $k = 1, \ldots, K$, is the dimension of the time-series. Note that in the social interaction detection task, $N$ is equal to the total number of prototypes in the training set, and in the social interaction categorization task, $N$ is equal to the number of sequences in the training set.

The augmentation of $\Phi$ from $N$ to $\hat{N}$ time series, with $\hat{N} = \Delta N$, is achieved
through adding the vector $\hat{\Phi}_n(\tau) = (\phi_{1,n}(\tau), \phi_{2,n}(\tau), \ldots, \phi_{K,n}(\tau))$ to the frame $\tau$ of the $n$-th time-series in $\Delta$ number of attempts. $\hat{\Phi}_n(\tau)$ is obtained as:

$$\hat{\Phi}_n(\tau) = [P_1, P_2, \ldots, P_K][\theta_{1,n}(\tau)\lambda_1, \theta_{2,n}(\tau)\lambda_2, \ldots, \theta_{K,n}(\tau)\lambda_K]^T,$$

where $P_k$ and $\lambda_k$ are the $k$-th eigenvector and eigenvalue of the $K \times K$ covariance matrix of feature values, respectively, and $\theta_{k,n}(\tau)$ is the aforementioned random variable. It is worth to mention that in the social interaction detection task, $K = 4$ and in the social interaction categorization task, $K = 32$. In the social interaction detection, since the facial expression is a variable with discrete values, we did not consider to alter it in the data augmentation. Instead, when we generated new samples of signals from an original signal, we only repeated the facial expression value of the original signal in the augmented signals. We did not consider to alter the facial expression vector neither in the social interaction categorization task, since the facial expression feature vector originally contains values of probabilities which must sum to 1 and altering them leads to a change in their essence. Instead, similar to the other tasks, we only repeated the facial expression feature vector of the original signal in the augmented signals.

### 6.1.3. Network structure and hyper-parameter optimization

Our LSTM network architecture is a three layer network consisting of the input layer, the hidden layer and the output layer, where the input layer has forward connections to all units in the hidden layer. In this work, full-BPTT is used for training of the network. The hidden layer contains various number of memory cells and corresponding gate units use inputs from other memory cells to decide whether to access certain information in its memory cell. The output layer receives connections only from memory cells. Each LSTM is composed of various numbers of memory cells and we used the well-known Stochastic Gradient Decent method (SGD) for optimization. A dropout layer is added between the hidden layers and the output layer to mitigate the overfitting problem which is a very common problem in training LSTM models. Both of the tasks in our hand are binary classification problem, thus, we used an output layer with a
single neuron and a sigmoid function to make 0 or 1 predictions for the two
classes in the problem. A log loss is used as loss function. Due to the higher
computational complexity of the gate specific dropout techniques in the hidden
layer, we did not use any of them. We performed grid-search for finding the best
combination of parameters for each classification task, separately. The studied
parameters for the grid-search are learning rate and momentum of the SGD
optimizer, dropout rate and the number of neurons of the LSTM in the hidden
layers of the network architecture and the batch size and number of epochs as
general parameters. We made log-uniform sampling over the following interval
of hyper-parameters: [0.0001,0.1] learning rate, [0.1,0.9] momentum, [0.0,0.9]
dropout rate, [10,200] number of neurons, [100,1000] batch size, and [10,100]
epochs.

6.2. Experimental results and discussion

As mentioned earlier, our approach towards social interaction analysis pri-
marily passes through representation of the social events in the format of time-
series, where every time-step represents features belonging to one frame of the
social event. Later, time-series are temporally analyzed relying on the power
of LSTM in temporal analysis of the time-series. As the set of the represen-
tative features for each task is composed of several independent features, we
explore different combinations of features, which are studied for each task in
our experiments in order to prove the optimal performance of the method.

6.2.1. Social interaction detection

In this task, four set of settings of social signals are explored as based on
different combinations of the distance feature, orientation feature, and the facial
expression feature as following:

- **SID1**: Distance + Yaw
- **SID2**: Distance + Yaw + Pitch + Roll
- **SID3**: Distance + Yaw + Facial expression
Table 2: Social interaction detection results

|               | ego-HVFF | SID1   | SID2   | SID3   | SID4   |
|---------------|----------|--------|--------|--------|--------|
| Precision     | 82.75%   | 80.76% | 88.49% | 88.59% | 91.66% |
| Recall        | 55.81%   | 64.61% | 76.92% | 77.69% | 84.61% |
| Accuracy      | 58.38%   | 61.62% | 75.00% | 75.58% | 82.55% |

- **SID4**: Distance + Yaw + Pitch + Roll + Facial expressions

SID1 is the baseline setting in which only presented features in our previous work \[3\] are studied. In SID2, pitch and roll in addition to yaw as the main indicator of face orientation in previous works are studied. SID3 follows the same pattern as SID1, but includes facial expression features as well to observe the effect of facial expressions in addition to commonly studied features for social interaction detection. Finally, SID4 includes all the discussed features for social interaction detection analysis. It is important to note that the data augmentation is only performed once for the complete 4-dimensional setting (SID4) and data in other settings is formed by selecting the required dimensions from the complete setting.

In Table 2, we report the obtained precision, recall and accuracy values for each of the above settings. Besides, we also compared our obtained results with the ego-HVFF model \[1\] as the unique method amongst state-of-the-art methods suitable for social interaction detection in egocentric photo-streams as discussed in Sec. 2. The best obtained results, in all terms of precision, recall and accuracy belong to the SID4 setting containing all the proposed features (distance, yaw, pitch, roll, facial expressions) for social interaction detection. Comparing SID1 with each of SID2 and SID3 shows that the incorporation of each of the other head orientation information and facial expression in the analysis leads to more robust social interaction detection, while facial expression shows to have a slightly stronger impact (SID3) than additional head orientations (SID2). Ego-HVFF only considers distance and yaw orientation (SID1)
Figure 8: Two examples to highlight the role of facial expression. Sequences are correctly classified employing SID3 and SID4 settings, and failed to be correctly classified employing SID1. For better observability in the cluttered scene, faces are shown by a green bounding box around them.

for social interactions detection. However as expected, temporal analysis of SID1 in sequence-level leads to more accurate social interaction detection than frame-level analysis of the sequences as it has been achieved through applying ego-HVFF on this dataset. In the social interaction detection task, all the social signals originate from the face appearance of the third-person. Therefore, face occlusions due to movements of the camera or the user itself, lead to social signals discontinuity. Analysis of the sequences in frame-level results in direct exclusion of occluded frames from the analysis while sequence-level analysis in format of time-series mitigates the social signals fragmentation impact by considering the relation among the rest of the frames of a sequence.

Fig. 8 and Fig. 9 are visual demonstrations of how facial expressions and additional head orientations aid in more robust social interaction detection. In Fig. 8a and Fig. 8b although the subjects are oriented towards the user and they are in relatively close proximity to the camera, we assume their neutral facial expressions were a determinant factor in helping the model to correctly classify them as not interacting with the user. Another scenario can be observed in Fig. 9a and Fig. 9b. In Fig. 9b, despite the close proximity of the subject to the user and although her yaw orientation goes towards the user, we assume the
uncommon pitch orientation of her head aided the model to correctly classify the sequence as not interacting with the user. Two failure cases of the detection model can be observed in Fig. 10. This could happen due to the uncommon head pose of the interacting people and their dominant neutral facial expression. Indeed in none of the examples, the interacting people are looking towards the user.
### Table 3: Social interaction categorization results

| Precision | HM-SVM | VGG-FT | SIC1 | SIC2 | SIC3 |
|-----------|--------|--------|------|------|------|
|           | 76.82% | 86.81% | 87.91% | 89.01% | **91.48%** |
| Recall    | 63.65% | 89.77% | 90.90% | 92.04% | **97.72%** |
| Accuracy  | 64.87% | 82.30% | 83.18% | 84.95% | **91.15%** |

#### 6.2.2. Social interaction categorization

In this task, environmental and facial expression features were considered as the representative features, so the following settings are considered for the temporal analysis:

- **SIC1**: Environmental (VGG)
- **SIC2**: Environmental (VGG-finetuned)
- **SIC3**: Environmental (VGG-finetuned) + Facial expressions

We assume that global features of an event, namely environmental features, have the greatest impact in the categorization of it. Therefore in this section, the first setting (SIC1) studies only environmental features which are extracted from the last fully connected layer of VGGNet trained over the Imagenet and preprocessed as explained in Sec. 4.1. VGGNet trained on the Imagenet is highly capable of grasping the general semantics in an image. However, fine-tuning the network for a specific task over relevant data for that task, adapts the pre-trained network to that specific purpose. Therefore, we assume the extracted features from the fine-tuned network ideally lead to better representation of the desired classification task. In SIC2, the environmental features are extracted in the same manner as SIC1, but from the fine-tuned VGGNet over the training set of the proposed dataset in this work. The features are preprocessed in the same manner as explained in Sec. 4.1. Fine-tuning the network is achieved through instantiation of the convolutional part of the model up to the
fully-connected layers and then training fully-connected layers on the photos of the training set. The last setting to be studied is SIC3, which explores jointly the effect of facial expressions as well as the environmental features in social interaction categorization.

In this work for social interaction categorization, our focus is mostly to study the evolution of considered relevant features along a sequence. Therefore, despite our choice of VGGNet pre-trained over Imagenet for feature extraction, without the loss of generality any other CNN architecture suitable for image feature extraction could be employed and finding the optimal CNN architecture was out of scope of this work. Moreover, the Imagenet dataset was preferred to a seemingly more relevant dataset such as Places [46] for environmental feature extraction of images. This is due to the narrow field of view of the Narrative camera where in the images captured by it, a scene is better observed by the set of visible objects in it rather than the wide view of the scene.

In Table 3, we report the precision, recall and accuracy values obtained for each setting of the aforementioned settings. Additionally, we compared our obtained results with HM-SVM [45] which is an applicable state-of-the-art method to our setting as this model similarly to ours extracts features in the egocentric setting and analyzes them in sequence-level but different to our proposed model, employs a HMM to model interaction sequences according to features to categorize them. To apply HM-SVM, the HMM is trained using our training set where features follow the SIC3 setting. The HM-SVM is later employed to label the interaction state. We also report achieved results by a baseline method, VGG-finetuned, in which we fine-tuned the VGG network on the photos of the training set in EgoSocialStyle and tested the trained model over the pool of photos in EgoSocialStyle test set. Thus, this model is also considered frame-level rather than sequence-level.

The obtained results suggest that, temporal analysis of environmental features extracted from fine-tuned VGGNet in SIC2 setting outperforms temporal analysis of environmental features extracted from VGGNet before fine-tuning in the SIC1 setting. Temporal analysis of fine-tuned features also outperforms
Figure 11: Two successful examples, emphasizing on the role of facial expressions in social interaction categorizations employing SIC3 setting. The method trained over mere general features employing SIC2 setting did not lead to the right categorization.

The frame-level analysis of fine-tuned features in VGG-FT which is also an indication of the importance of temporal analysis of features in this task. The combination of environmental features extracted through fine-tuned VGG network and feature vector of facial expressions probabilities leads to the highest performance for categorization of social interactions into formal and informal meetings. HM-SVM is trained and tested with features in the SIC3 setting. However, the obtained results suggest that the LSTM demonstrates more power in modeling the problem at hand than the HMM.

It is worth to note that due to the extensive amount of data that end-to-end models need for training (few million data) and our limited number of image sequences in the dataset, we did not consider to design our proposed model in an end-to-end fashion. Indeed, making use of pre-trained networks, like emotion, makes a more effective use of the resources when the available data is small compared with the amount of data needed to train the individual sub-networks.

In Fig. 11a two sequences are shown in which the aggregation of facial expressions with the general environmental features employing SIC3 leads to the correct categorization of them. In Fig. 11b although the environment is the indicator of a formal meeting, we assume the variant facial expressions of the subject aids the model to correctly classify it as an informal meeting. On
Figure 12: Two failure examples of the model in social interaction categorizations. We assume misleading environmental features in 12a and neutral facial expressions of the subject in 12b led to these failure cases.

the contrary, in Fig. 11b despite the scene not implying a formal meeting, we assume the dominant neutral facial expression of the subject leads to the correct categorization of the sequence as a formal meeting. Fig. 12 shows two cases where the model fails to correctly categorize social interactions due to misleading features transmitted from the scene. Both Fig. 12a and Fig. 12b are informal gatherings which are classified incorrectly as formal meetings. We assume in Fig. 12a the model confuses the menu with a piece of paper which is an important characteristic of a formal meeting. We also assume in Fig. 12b the invariant neutral facial expression of the person leads the model to fail.

6.2.3. Social pattern characterization

To illustrate the ability of the proposed framework for social pattern characterization of an individual, face clustering is applied on the test set. A total number of 83 clusters is obtained, which is almost double the size of the total number of prototypes in the test set. The largest cluster contains 77 number of faces from 5 number of sequences belonging to the same person in various social events. The different statistics of the social interactions of the user, as well as those related to the most frequently interacted person are provided in Table 4. The social pattern of the user over one week according to the obtained
results from clustering and inference to their types is visualized in Fig. 13. Social interactions are shown by horizontal colored lines, where the interaction boundaries are shown by circles for informal meetings and squares for formal meetings. Different colors correspond to different persons. Re-occurring people in one social event are shown with parallel lines within the same interval.

From our observation, it can be concluded that during the observation interval the user interacted with the most frequently interacting person in his social life 5 times, in 4 different days, 4 times of which occurred during informal meetings. An interesting observation is that in a cluster containing different sequences, a sequence may belong to a formal or informal meeting which implies the user may have different types of interaction with the same person in various social events. On the other side, according to the results, the generic social trend of the user is correlated to the person-specific one (0.05 difference in both formal and informal social trends). Generic diversity of social interaction of the user is relatively high (87%) which means the user is almost equally involved in both categories of social interactions, although expectedly has more informal social interactions since an informal social interaction can occur at any time without any planning, while for formal social interactions normally planning is involved. As it can be observed in Fig. 13, informal social interactions of the user are happening at almost any time of the day and the formal social interactions are
Table 4: Social pattern characterization results

|                  | F-Formal | F-Informal | A-Formal | A-Informal | D     | L       |
|------------------|----------|------------|----------|------------|-------|---------|
| Generic          | 0.83     | 2.50       | 0.25     | 0.75       | 0.87  | 25.19±1.32 |
| Person-specific  | 0.25     | 1.00       | 0.20     | 0.80       | 0.59  | 18.80±0.96 |

normally happening during the middle of the day.

7. Conclusions

In this work, we proposed a complete pipeline for social pattern characterization of a user wearing a wearable camera for a long period of time (e.g. a month), relying on the visual features transmitted from the captured photo-streams. Social pattern characterization is achieved through first, the detection of social interactions of the user and second, their categorization. In the end, different appearances of interacting with the wearer individuals in different social events are localized through face clustering to directly derive the frequency and the diversity of social interactions of the wearer with each individual observed in the images. In the proposed method, social signals for each task are presented in the format of multi-dimensional time-series and LSTM is employed for the social interaction detection and categorization tasks. A quantitative study over different combination of features for each task is provided, unveiling the impact of each feature on that task. Evaluation results suggest that in comparison to the frame-level analysis of the social events, sequence-level analysis employing LSTM leads to a higher performance of the model in both tasks.

To the best of our knowledge, this is the first attempt at a comprehensive and unified analysis of social patterns of an individual in either ego-vision or third-person vision. This comprehensive study can have important applications in the field of preventive medicine, for example in studying social patterns of patients affected by depression, of elderly people and of trauma survivors.
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References

[1] Aghaei, M., Dimiccoli, M., Radeva, P., 2015. Towards social interaction detection in egocentric photo-streams, in: Eighth International Conference on Machine Vision, International Society for Optics and Photonics. pp. 987514–987519.

[2] Aghaei, M., Dimiccoli, M., Radeva, P., 2016a. Multi-face tracking by extended bag-of-tracklets in egocentric photo-streams. Computer Vision and Image Understanding 149, 146–156.

[3] Aghaei, M., Dimiccoli, M., Radeva, P., 2016b. With whom do I interact? detecting social interactions in egocentric photo-streams, in: Pattern Recognition, 23rd International Conference on, IEEE. pp. 2959–2964.

[4] Aghaei, M., Dimiccoli, M., Radeva, P., 2017. All the people around me: face discovery in egocentric photo-streams. International Conference on Image Processing, International Conference on .

[5] Alletto, S., Serra, G., Calderara, S., Cucchiara, R., 2015. Understanding social relationships in egocentric vision. Pattern Recognition 48, 4082–4096.

[6] Amato, G., Debole, F., Falchi, F., Gennaro, C., Rabitti, F., 2016. Large scale indexing and searching deep convolutional neural network features, in: International Conference on Big Data Analytics and Knowledge Discovery, Springer. pp. 213–224.
[7] Barsoum, E., Zhang, C., Ferrer, C.C., Zhang, Z., 2016. Training deep networks for facial expression recognition with crowd-sourced label distribution. ACM International Conference on Multimodal Interaction.

[8] Berry, E., Kapur, N., Williams, L., Hodges, S., Watson, P., Smyth, G., Srinivasan, J., Smith, R., Wilson, B., Wood, K., 2007. The use of a wearable camera, sensecam, as a pictorial diary to improve autobiographical memory in a patient with limbic encephalitis: A preliminary report. Neuropsychological Rehabilitation 17, 582–601.

[9] Betancourt, A., Morerio, P., Regazzoni, C.S., Rauterberg, M., 2015. The evolution of first person vision methods: A survey. Transactions on Circuits and Systems for Video Technology 25, 744–760.

[10] Bolanos, M., Dimiccoli, M., Radeva, P., 2017. Toward storytelling from visual lifelogging: An overview. Transactions on Human-Machine Systems 47, 77–90.

[11] Choi, W., Chao, Y.W., Pantofaru, C., Savarese, S., 2014. Discovering groups of people in images, in: European Conference on Computer Vision, Springer. pp. 417–433.

[12] Cristani, M., Bazzani, L., Paggetti, G., Fossati, A., Tosato, D., Del Bue, A., Menegaz, G., Murino, V., 2011. Social interaction discovery by statistical analysis of F-formations., in: BMVC, p. 4.

[13] Cristani, M., Raghavendra, R., Del Bue, A., Murino, V., 2013. Human behavior analysis in video surveillance: A social signal processing perspective. Neurocomputing 100, 86–97.

[14] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L., 2009. Imagenet: A large-scale hierarchical image database, in: Computer Vision and Pattern Recognition, Conference on, IEEE. pp. 248–255.
[15] Dhand, A., Dalton, A.E., Luke, D.A., Gage, B.F., Lee, J.M., 2016. Accuracy of wearable cameras to track social interactions in stroke survivors. Journal of Stroke and Cerebrovascular Diseases.

[16] Dimiccoli, M., Bolaños, M., Talavera, E., Aghaei, M., Nikolov, S.G., Radeva, P., 2016. Sr-clustering: Semantic regularized clustering for egocentric photo streams segmentation. Computer Vision and Image Understanding.

[17] Fathi, A., Hodgins, J.K., Rehg, J.M., 2012. Social interactions: A first-person perspective, in: Computer Vision and Pattern Recognition, Conference on, IEEE. pp. 1226–1233.

[18] Gan, T., Wong, Y., Zhang, D., Kankanhalli, M.S., 2013. Temporal encoded F-formation system for social interaction detection, in: Proceedings of the 21st ACM international conference on Multimedia, ACM. pp. 937–946.

[19] Girshick, R., Donahue, J., Darrell, T., Malik, J., 2014. Rich feature hierarchies for accurate object detection and semantic segmentation, in: Proceedings of the conference on computer vision and pattern recognition, pp. 580–587.

[20] Granholm, E., Ben-Zeev, D., Fulford, D., Swendsen, J., 2013. Ecological momentary assessment of social functioning in schizophrenia: impact of performance appraisals and affect on social interactions. Schizophrenia research 145, 120–124.

[21] Groh, G., Lehmann, A., Reimers, J., Frieß, M.R., Schwarz, L., 2010. Detecting social situations from interaction geometry, in: Social Computing, Second International Conference on, IEEE. pp. 1–8.

[22] Hess, U., Bourgeois, P., 2010. You smile–I smile: Emotion expression in social interaction. Biological psychology 84, 514–520.

[23] Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural computation 9, 1735–1780.
[24] Hodges, S., Berry, E., Wood, K., 2011. Sensecam: A wearable camera that stimulates and rehabilitates autobiographical memory. Memory 19, 685–696.

[25] Hudson, P.B., Hudson, S.M., Craig, R.F., 2006. Distributing leadership for initiating university-community engagement.

[26] Hughes, G., 1968. On the mean accuracy of statistical pattern recognizers. transactions on information theory 14, 55–63.

[27] Hung, H., Kröse, B., 2011. Detecting F-formations as dominant sets, in: Proceedings of the 13th international conference on multimodal interfaces, ACM. pp. 231–238.

[28] Jia, X., Gavves, E., Fernando, B., Tuytelaars, T., 2015. Guiding the long-short term memory model for image caption generation, in: Proceedings of the International Conference on Computer Vision, pp. 2407–2415.

[29] Kendon, A., 1976. The F-formation system: The spatial organization of social encounters. Man-Environment Systems 6, 291–296.

[30] Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. Imagenet classification with deep convolutional neural networks, in: Advances in neural information processing systems, pp. 1097–1105.

[31] Ma, S., Sigal, L., Sclaroff, S., 2016. Learning activity progression in lstms for activity detection and early detection, in: Proceedings of the Conference on Computer Vision and Pattern Recognition, pp. 1942–1950.

[32] Mangrum, F.G., Fairley, M.S., Wieder, D.L., 2001. Informal problem solving in the technology-mediated work place. The Journal of Business Communication (1973) 38, 315–336.

[33] Muncy, R., 2001. Disconnecting: Social and civic life in america since 1965. Reviews in American History 29, 141–149.
[34] Narayan, S., Kankanhalli, M.S., Ramakrishnan, K.R., 2014. Action and interaction recognition in first-person videos, in: Proceedings of the Conference on Computer Vision and Pattern Recognition Workshops, pp. 512–518.

[35] Palispis, E., 2007. Introduction to Sociology and Anthropology. Manila: Rex Book Store, Inc.

[36] Pascanu, R., Mikolov, T., Bengio, Y., 2013. On the difficulty of training recurrent neural networks. ICML (3) 28, 1310–1318.

[37] Setti, F., Lanz, O., Ferrario, R., Murino, V., Cristani, M., 2013. Multi-scale F-formation discovery for group detection, in: International Conference on Image Processing, IEEE. pp. 3547–3551.

[38] Setti, F., Russell, C., Bassetti, C., Cristani, M., 2015. F-formation detection: Individuating free-standing conversational groups in images. PloS one 10, e0123783.

[39] Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[40] Soo Park, H., Shi, J., 2015. Social saliency prediction, in: Proceedings of the Conference on Computer Vision and Pattern Recognition, pp. 4777–4785.

[41] Steinlin, M., 2005. Knowledge management feng shui: designing knowledge sharing-friendly office space. Knowledge Management for Development Journal 1.

[42] Wong, S.C., Gatt, A., Stamatescu, V., McDonnell, M.D., 2016. Understanding data augmentation for classification: when to warp?, in: Digital Image Computing: Techniques and Applications (DICTA), 2016 International Conference on, IEEE. pp. 1–6.
Woodberry, E., Browne, G., Hodges, S., Watson, P., Kapur, N., Woodberry, K., 2015. The use of a wearable camera improves autobiographical memory in patients with Alzheimer’s disease. Memory 23, 340–349.

Xiong, Y., Quek, F., 2005. Meeting room configuration and multiple camera calibration in meeting analysis, in: Proceedings of the 7th international conference on Multimodal interfaces, ACM. pp. 37–44.

Yang, J.A., Lee, C.H., Yang, S.W., Somayazulu, V.S., Chen, Y.K., Chien, S.Y., 2016. Wearable social camera: Egocentric video summarization for social interaction, in: Multimedia & Expo Workshops, International Conference on, IEEE. pp. 1–6.

Zhou, B., Lapedriza, A., Xiao, J., Torralba, A., Oliva, A., 2014. Learning deep features for scene recognition using places database, in: Advances in neural information processing systems, pp. 487–495.