Enhancing Human–Robot Interaction through Group Emotion Recognition

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***Abstract* - This paper explores the field of human–robot interaction (HRI), focusing on the complicated relationship between emotions, decision making (DM), and robot behaviors. Emotions are essential to effective communication and interaction, requiring the development of emotion recognition systems in robots. This paper explores individual and group emotion recognition, including micro and macro expressions. This paper analyzes group emotion dynamics, encompassing phenomena such as emotional contagion, convergence, and social influence, to understand how emotions are combined within collective settings. This paper introduces the concept of group emotion recognition (GER), providing a framework for recognizing emotions within groups. GER involves proximity metrics, emotion classification, and entropy-based analysis to quantify emotion diversity. This paper discusses DM based on GER driven by positive or negative emotion labels, highlighting the adaptability and sensitivity required for effective Human-Robot Interaction HRIs. This paper addresses ethical considerations regarding the use of emotion recognition technology throughout, emphasizing responsible implementation. Overall, this work lays a solid foundation for advancing the field of HRI by integrating emotion recognition and DM to create emotionally intelligent, socially aware robots.**

Index items: human–robot interaction (HRI), group emotion recognition (GER), individual emotion recognition (IER), decision making (DM)

I. INTRODUCTION

The field of human–robot interaction (HRI) has witnessed remarkable advancements in recent years, propelled by the integration of innovative technologies and a deeper understanding of human psychology and behavior. At the heart of this interdisciplinary effort lies the intricate interplay between emotions, decision making (DM), and behaviors exhibited by robots. Emotions are a fundamental aspect of human communication and interaction, playing an essential role in shaping social dynamics, building rapport, and conveying intentions. Recognizing and interpreting these emotional signals is crucial for robots to engage effectively with humans, understand their needs, and respond in a manner that reflects their emotional state. Equally important is DM, which drives the actions and behaviors of robots in response to the ever-changing contexts of human interactions [1]. Decisions made by robots extend beyond simple algorithms; they encompass a good understanding of human emotions, preferences, and social signs. Effective DM empowers robots to fit their responses, adapt to dynamic environments, and enhance the overall quality of HRIs. The primary goal of this theoretical chapter is to establish a robust, comprehensive understanding that bridges the domains of emotion recognition and DM within the field of HRI. By exploring the theoretical underpinnings of these essential components, this article paves the way for the practical implementation and experimental validation of an approach: HRI DM based on group emotion recognition (GER). This paper begins by exploring the fundamentals of individual emotion recognition (IER), dissecting the mechanisms through decoding subtle emotional cues from facial expressions. The challenges and nuances behind accurate emotion recognition are explored, acknowledging the complexities introduced by cultural diversity, context dependencies, and the intricacies of human emotional expression. Transitioning from individual emotions to group emotions needs exploring the intricacies of emotional dynamics within collective settings. Concepts such as emotional effect, convergence, and social influence focus on how individual emotions are combined to form collective emotional states. This exploration ends in the introduction of GER, an innovative paradigm that extends emotion recognition to encompass multiple individuals within a scene. These explorations regard the role of entropy as a powerful metric for quantifying the diversity and uncertainty within emotional distributions and demonstrate how entropy-based analysis enhances the understanding of emotional dynamics and shapes adaptive DM in HRI scenarios. The core of the theoretical framework in Figure 1 involves determining GER, emotion classification, DM, and the integration of a chatbot as an example of HRI. GER is the foundation for recognizing emotions in group settings. Emotion classification categorizes group emotions into positive or negative. DM utilizes these emotions to trigger appropriate robot behaviors, such as moving away for negative emotions or initiating conversations for positive emotions. The chatbot serves as an empathetic, context-aware interface for seamless human–robot communication, enhancing the overall HRI experience. This interconnected approach lays the groundwork for subsequent chapters that explore practical implementation, experimental validation, and real-world implications.

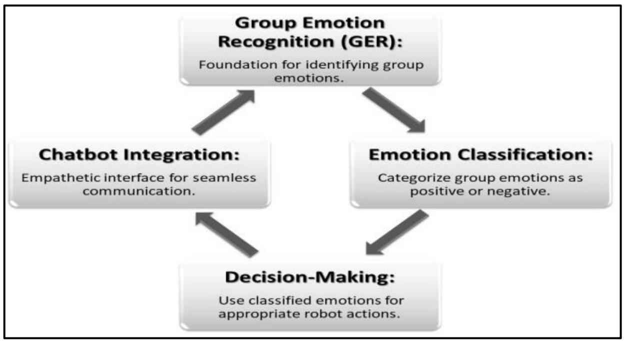

Fig. 1 GER, emotion classification, DM, and chatbot relation

II. RELATED WORKS

Zhang (2013) proposed neural network-based facial emotion recognition and semantic-based topic detection, enhancing natural interaction [2]. Cid (2014) developed a real-time system for facial expression recognition and imitation in affective HRI [3]. Building on this, researchers in 2015 proposed a multimodal emotion recognition approach that combines visual and auditory information processing, achieving the robust recognition of emotional states [4]. In 2018, Chen introduced a SoftMax regression-based deep sparse autoencoder network for facial emotion recognition, enhancing emotion detection in HRI [5]. Spezialetti (2020) discussed the importance of endowing robots with emotional intelligence, focusing on emotion recognition models and modalities, the role of facial expressions, body poses, voice, brain activity, and physiological responses [1]. Mohammed (2020) surveyed emotion recognition for HRI, discussing challenges and sensing channels [6]. Finally, Chen (2020) proposed the two-layer fuzzy multiple random forest for speech emotion recognition, emphasizing the fusion of personalized and nonpersonalized features for stable emotion recognition [7]. Furthermore, Chen (2021) introduced AdaBoost-KNN with adaptive feature selection for dynamic emotion recognition in HRI, improving real-time emotion understanding [8]. Lastly, Filippini (2021) presented a convolutional-neural-network (CNN)-based facial expression recognition model integrated into the NAO robot, enhancing the awareness of human facial expressions [9]. Additionally, Toichoa Eyam (2021) introduced the emotion-driven adaptation of robot parameters in collaborative applications and bridging emotional gaps between humans and robots [10]. A systematic review by Stock-Homburg (2022) offered insights into humans' recognition and responses to artificial emotions in HRI [11]. Valagkouti (2022) focused on affective computing and game-based environmental awareness using NAO robots, demonstrating real-world applications [12]. These studies collectively contribute to the advancement of HRI through GER, addressing challenges and improving the naturalness of HRIs.

III. EMOTION RECOGNITION

Understanding and interpreting human emotions is a complex but essential task in the field of HRI. IER is the foundational step in this process, whose objective is to detect and classify accurately emotions expressed by an individual through facial expressions. This recognition serves as a fundamental building block for extending emotion analysis to group settings and influencing robot behaviors and interactions [13]. At the core of IER is the analysis of facial expressions with a wealth of emotional information, ranging from subtle micro expressions to overt macro expressions. In the field of IER, distinguishing between micro and macro expressions is important. Micro expressions are fleeting, involuntary facial movements that occur in response to genuine emotions. They often provide authentic cues about a person's emotional state but are challenging to capture due to their rapid nature. By contrast, macro expressions are more sustained facial expressions that are aligned with the underlying emotional state, as shown in Figure 2 [14]. The following are examples of micro and macro expressions for each of the six basic emotions based on real-life scenarios:

❖ ***Fear:***

* Micro expression: A person briefly widens his/her eyes and raises his/her eyebrows when hearing a sudden loud noise.

* Macro expression: A person screams and jumps back when unexpectedly encountering a snake on a hiking trail.

❖ ***Surprise:***

* Micro expression: A person widens his/her eyes in a split second when opening a present and finding an unexpected item inside.

* Macro expression: A person exclaims loudly and jumps out of his/her chair when walking into a surprise birthday party thrown for him/her.

❖ ***Anger:***

* Micro expression: A person subtly clenches his/her jaw and briefly narrows his/her eyes when receiving frustrating news via email.

* Macro expression: A person shouts and slams the door in anger when discovering his/her car has been towed without notice.

❖ ***Disgust:***

* Micro expression: A person momentarily wrinkles his/her nose when smelling a foul odor while passing a garbage dumpster.

* Macro expression: A person visibly gags and pushes away a plate of spoiled food after taking a bite.

❖ ***Sadness:***

* Micro expression: A person briefly turns down the corners of his/her mouth and his/her lower lip slight trembles when receiving a sad text message.

* Macro expression: A person's eyes fills with tears, and he/she sobs uncontrollably when hearing about the loss of a loved one.

❖ ***Happiness:***

* Micro expression: A person flashes a quick, genuine smile when complimented by his/her crush.

* Macro expression: A person bursts into laughter, hugs his/her friends, and dances around with joy after learning he/she has won a major lottery jackpot.

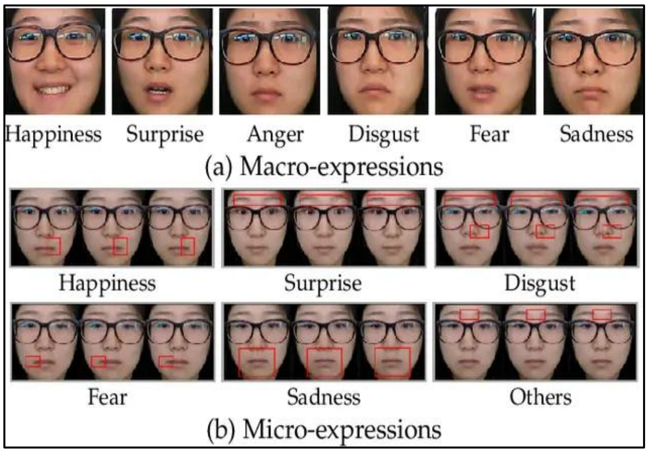

Fig. 2 Macro and micro expression

In the domain of IER, numerous challenges and complexities can remarkably affect the accuracy and reliability of emotion recognition systems. These challenges encompass a range of issues, including occlusions such as unclear facial features, variations in lighting conditions, diverse and nuanced facial expressions, rapid temporal dynamics of emotions, subjectivity influenced by individual and cultural differences, the need for cross-domain generalization, data imbalance in biased datasets, ambiguity in emotion categorization, contextual dependency of emotions, and ethical considerations related to privacy and potential exploitation. Addressing these challenges is essential for the development and deployment of effective, responsible IER technologies.

A. Dynamic Group Emotion Recognition

GER extends conventional emotion recognition approaches from individual emotions to the complexities of group emotions, offering potential benefits in enhancing user engagement, personalizing interactions, improving group dynamics, and developing social acceptance of robots in HRI scenarios.

B. Complexity of Group Emotions

To explore deeper into the field of GER, a rich, complicated mixture of emotional dynamics that emerges within a social environment is faced. The transition from understanding individual emotions to comprehending the complexities of group emotions shows an interplay of psychological and social phenomena. This section aims to clarify the multifaceted nature of group emotions, exploring concepts such as emotional contagion, emotional convergence, and social influence, which collectively contribute to the formation of collective emotional states. By unraveling these dynamics, essential insights are gained into the intricacy and depth of emotions within groups, an understanding essential for effectively capturing the accurate landscape of emotions in this context [15].

A. Emotional Contagion: Emotional contagion is the phenomenon where the emotions of one individual within a group can spread and "infect" other individuals, leading to a shared emotional experience. This contagion occurs through nonverbal cues, facial expressions, body language, and vocal intonations. When a person expresses a strong emotion, such as excitement, happiness, or anxiety, those around him/her may unconsciously mirror and adopt similar emotional states. In a group setting, emotional contagion can create a ripple effect, amplifying and propagating emotions across individuals.

B. Emotional Convergence: Emotional convergence explores the tendency of individuals within a group to synchronize their emotional states over time. As group members interact and share experiences, their emotions become aligned, resulting in the convergence of emotional expressions. This convergence is driven by the human inclination to seek emotional harmony and maintain social cohesion. Emotional convergence can lead to the amplification of shared emotions and the emergence of a dominant emotional theme within the group. In collaborative tasks or social interactions, emotional convergence can shape the collective mood and influence decision-making processes.

C. Social Influence and Emotional Framing: The concept of social influence plays an essential role in shaping group emotions. Individuals within a group are affected by not only their internal emotional states but also the emotional expressions and behaviors of others. Social influence can stem from perceived social norms, group dynamics, and the desire for social approval. Emotional framing, where individuals interpret and label emotions based on social signs and context, further contributes to the flexibility of group emotions. For instance, if a leader within a group displays interest and hopefulness, others may adopt similar emotions, thereby contributing to a positive group atmosphere.

D. Emergence of Collective Emotional States: As emotional contagion, emotional convergence, and social influence intertwine, collective emotional states emerge as a result of complex interactions. These collective emotional states transcend the sum of individual emotions, giving rise to a unique emotional climate that characterizes the group as a whole. The emergent emotional state can influence group cohesion, DM, and overall group dynamics. The collective emotions that emerge from a crowd at a sporting event, a team working on a project, or an audience at a concert define the shared experience and interactions within the group. In Figure 3, Panel A represents the individual emotions, including one subtype of individual emotions, namely, group-based emotions, whereas Panel B represents collective emotions. Collective emotions are regarded as many individual emotions (represented by the smaller circles). Collective emotions unfold as a result of emotional interactions among individuals. These interactions can involve either nongroup or group-based individual emotions.

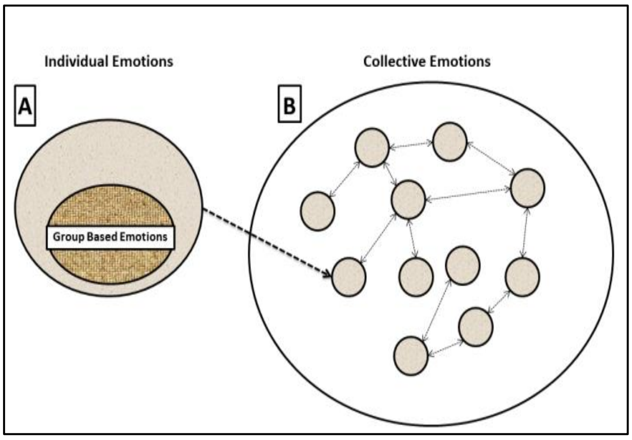

Fig. 3: Collective emotions

C. Importance of GER

GER represents a paradigm in the field of HRI that extends the conventional emotion recognition approaches from individual emotions to emotions within a collective group setting. By recognizing and understanding the emotional environment of a group, GER opens up new possibilities and potential benefits for HRI [16]. These potential benefits and their effects on various applications are explored.

1) *Enhancing User Engagement Explanation:*
GER enhances user engagement in HRI by accurately recognizing and responding to group emotions. Emotional interactions foster a strong connection between humans and robots, resulting in more enjoyable and emotionally meaningful interactions.

2) *Personalizing Interaction Explanation:*

GER enables personalized responses based on individual emotional states within a group. Robots adapt behaviors to cater to unique emotional needs, creating more individualized interactions. Users feel valued and understood, strengthening the bond between humans and robots.

3) *Improving Group Dynamic Explanation:*
GER captures emotions of group members, identifying trends and dynamics. This understanding fosters harmonious interactions, resolves conflicts, and promotes positive emotional states within the group.

4) Supporting Emotional Regulation Explanation: GER detects emotional fluctuations within a group, aiding emotional regulation. Robots adjust behaviors to diffuse tension or provide support during conflicts, enhancing group emotional wellbeing.

5) *Enhancing Social Acceptance of Robot Explanation:*
Integrating GER into robot behaviors increases social awareness and emotional sensitivity. Robots demonstrate a deeper understanding of human emotions, potentially leading to greater acceptance of robots in various contexts.

6) *Facilitating Human–Robot Collaboration Explanation:*
In collaborative scenarios, GER comprehends emotions among team members. Robots fulfill roles that support group emotional needs, enhancing teamwork and cooperation.

7) Enabling Emotional Support in Group Context Explanation: In therapy or support groups, GER identifies and empathizes with the emotional states of multiple individuals simultaneously. Robots provide emotional support and comfort to the entire group, contributing to an encouraging atmosphere.

8) *Supporting Psychosocial Wellbeing Explanation:*
GER-equipped robots support emotional wellbeing in groups. In therapy, robots adapt interactions based on emotional states, offering comfort and validation.

D. GER Calculations

In GER determination, the initial step involves localizing faces within each frame and calculating proximity metrics to evaluate the importance of these faces. This step includes determining the number of faces in a frame and computing metrics such as the largest face and the nearest face using Euclidean distance calculations. Formally, for a face "i" in frame "t" with coordinates (x_i, y_i) relative to the group's center (x_c, y_c), the distance "d_i"

between face "i" and the group's center is calculated as follows:

$$d_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \quad \text{………………………(1)}$$

These proximity metrics provide crucial insights into the spatial dynamics of the group, which are essential for understanding group emotions. Then, in the GER procedure, the pretrained CNN model is applied to recognize the emotions expressed by each individual detected face in every frame. This recognition produces emotion labels for each face, which are a serious component for further analysis. Once emotions labels are assigned to each face within a frame, the largest faces and nearest faces are calculated to replace the determined face with the corresponding emotion label. Then, the probability distribution of all obtained emotions within the group is computed. This distribution helps evaluate the diversity of emotions expressed. To quantify this diversity, the concept of entropy, drawn from information theory, is introduced. Entropy measures the uncertainty or diversity of a distribution, which reflects the diversity of emotions within the group in this context [17]. The following steps are taken to calculate the entropy of the emotion labels:

- "E" is the set of emotion labels: *E*={*happy*, *surprise*, *sad*, *fear*, *disgust*, *angry*}.
- "N" represents the total number of faces detected in the frame.
- "n_e" signifies the number of faces with emotion label "e," where "e" is an element of the set "E."
- The probability distribution of emotion labels is calculated as follows:

$$P_e = \frac{n_e}{N} \quad \text{for each "e" in "E"} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

- The entropy of the emotion labels distribution is calculated as follows:

$$Entropy\_Value = -\sum P_e * log_2(P_e) \qquad \ldots\ldots\ldots\ldots\ldots (3)$$

- The entropy value increases with greater diversity or uncertainty in the distribution of emotion labels within the group, whereas it decreases when a dominant or focused emotion is expressed by the group. These steps collectively form a comprehensive approach to understanding and quantifying the emotions within a group context. The mean (average) GER value for the scene is calculated by adding all GER values for all frames within that scene and dividing the sum by the number of frames in the scene:

$$\text{Mean}_{\text{GER}} = \frac{\sum \text{GER values for all frames}}{\text{Number of frames in the scene}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

In summary, GER introduces a range of potential benefits for HRI scenarios. By recognizing and understanding the emotions within a group setting, robots can enhance user engagement, personalize interactions, improve group dynamics, support emotional regulation, and foster social acceptance. Additionally, GER enables robots to play a more active and adaptive role in collaborative settings and provide emotional support in various group contexts. Overall, GER holds promise for enriching the quality of HRIs and creating more emotionally intelligent and socially aware robots.

IV. GER Analysis

To analyze emotional dynamics in group scenarios' shape, a dataset known as the ROS/Gazebo Generated Dataset plays a fundamental role in exploring emotions within HRI. The ROS/Gazebo Generated Dataset consists of constructed image and video datasets of 23,222 images categorized into six classes of emotions (happy, sad, angry, surprise, disgust, and fear) and two simulated scenarios for the video datasets. These datasets are methodically prepared, standardized, and augmented to support CNN model training and testing in the context of HRI and GER [18]. The focus of research is to enable HRIs and DM based on group emotions. To accomplish this, a systematic approach needs to be employed, starting with the creation of a repository designed to store critical information required for emotion classification [19]. This information includes the frame file name, the number of detected faces in each frame, the emotions associated with each individual detected face, the probability distribution of emotions, entropy calculations, and information regarding the largest face, nearest face, and group scenes, as shown in Figure 4. To simplify processing and facilitate the efficient analysis of the extracted frames from a video, 10 repeated frames are collected into a single scene.

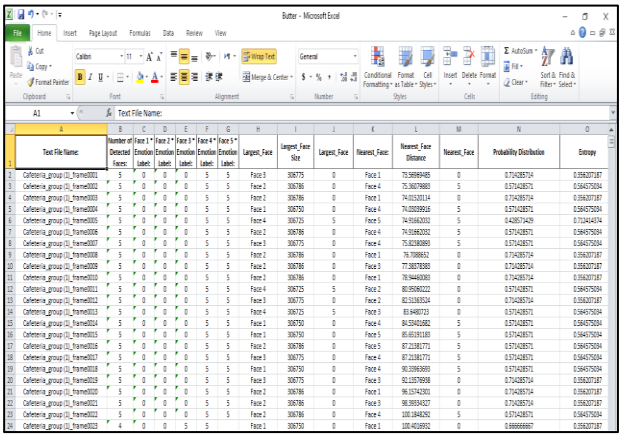

Fig. 4 View of samples from the main dataset repository

A. Face Localization via Proximity Metrics

The determination of GER starts with the specific localization of faces within each frame, accompanied by essential calculations to estimate the importance of these faces. This step involves determining the number of faces present in a frame and subsequently quantifying metrics such as the largest face and the nearest face using Euclidean distance calculation, which facilitates measuring the spatial relationship between detected faces and the center of the frame of the group of multiple faces. These proximity metrics provide valuable insights into the spatial dynamics of the group and play an essential role in determining group emotions.

B. Labeling Faces BY Individual Emotions

The next stage in the GER procedures involves the application of the pretrained CNN model to recognize the emotions expressed by each individual detected face in every frame. This process yields emotion labels for each face, a critical component for subsequent analysis.

C. Entropy Calculation thru Emotion Diversity

With the emotion labels determined for each face within a frame, the probability distribution of emotions must be calculated to enable understanding the diffusion of different emotions within the group. To measure the collective emotion of a group, the concept of entropy, a fundamental concept from information theory, is introduced, as shown previously in Section 4.3. The entropy value increases with greater diversity or uncertainty in the distribution of emotion labels and decreases when a dominant or focused emotion is shown by the group.

D. GER Classification

The algorithm below provides a structured approach to classify emotions within group scenarios based on facial expressions and spatial indications. The algorithm can be implemented in an HRI system to make informed decisions and to adapt to the emotional dynamics of the group in the ROS/Gazebo Generated Video Dataset [18] to obtain 1,458 frames:

Algorithm 1: GER

Input: Detected faces in a frame and pretrained attention CNN model

Output: GER score

Begin

1. Emotion Recognition:

- Utilize a pretrained attention CNN model for emotion recognition.

- For each detected face in a frame, obtain the following emotion labels:

(0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, and 5=Surprised)

2. Spatial Relationship Analysis:

- Compute the Euclidean distance between each detected face and the center of the group based on bounding boxes $d_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$.

- Calculate proximity metrics to understand the spatial relationships.

3. Emotion Label Refinement:

- Replace emotion labels for the largest face and nearest face in the frame.

- Ensure each detected face is associated with an emotion label.

4. Emotion Distribution Metrics:

- Compute the probability distribution P_e of emotion labels n_e within the group $NP_e = \frac{n_e}{N}$.

- Use this distribution to calculate entropy, a measure of diversity in emotions $H(X) = -\sum_{i=1}^{n} p(x_i) log_2(p(x_i))$.

5. Entropy Thresholding:

- Determine a suitable threshold for entropy based on the median value among the distributed values of entropy obtained from 1,458 frames.

- This threshold categorizes scenes based on the frame entropies of detected face emotions.

6. Emotion Consistency Analysis:

- Compare the computed entropy value with the predefined threshold.

- Determine if the frame exhibits clear, consistent emotions or diverse, uncertain emotions.

7. GER Score Calculation:

- Calculate the GER score by combining proximity metrics and entropy $Mean_{GER} = \frac{\sum GER\ values\ for\ all\ frames}{Number\ of\ frames\ in\ the\ scene}$.

8. Finalization:

- Assign the corresponding emotion label to the largest face and the nearest face.

- Calculate the probability distribution for these emotion labels.

- Compute the entropy based on this distribution.

Result: The GER score reflects the overall emotional dynamics of the group in the frame.

End

E. Identifying GER_Label

The last step involves identifying the GER_Label, which characterizes the overall emotional state of a scene consisting of multiple frames (typically 10 frames per scene). The process unfolds in the following Algorithm steps:

Algorithm 2: Calculate and Categorize GER for Scenes

Input: List of GER values for frames and predefined threshold

Output: Categorized GER values for scenes (positive or negative)

Begin

1. GER Calculation for Frames:

- Utilize the algorithm mentioned earlier to calculate the GER for each frame, considering weighted proximity and entropy.

- Append each calculated GER to the list of GER values for frames.

2. Scene Aggregation:

- For scenes consisting of every 10 frames or fewer, follow the steps below:

- Calculate a summary statistic to assess the variability or dispersion of emotions within that scene.

- Gather the last remaining frames in the repository to form one scene, even if they are less than 10 frames.

- Calculate the average GER value for the scene by adding all GER values for the frames within that scene and dividing the sum by the number of frames in the scene.

3. Threshold Comparison:

- Compare the aggregated GER value for the scene with a predefined threshold value.

- If the aggregated GER <= 0.564575034,

- categorize the GER value for the scene as positive.

- If the aggregated GER > 0.564575034,

- categorize the GER value for the scene as negative.

Result: Categorized GER values for scenes (positive or negative)

End

This structured approach provides a comprehensive evaluation of emotional dynamics within scenes, facilitating improvement calculations of group emotions during HRIs. This approach provides robots the capability to estimate the emotional state of groups and make context-aware decisions effectively, as shown in Figure 5.

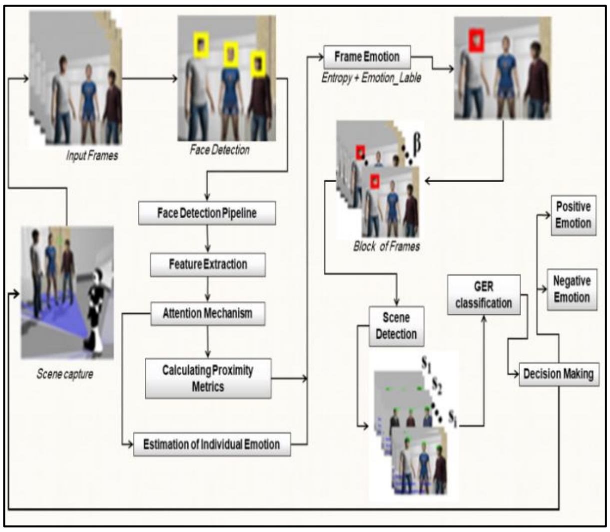

Fig. 5 GER estimation

IV.VII. DM

Creating a decision-making procedure for a social robot based on the positive or negative labeling of GER is a critical step to ensure appropriate HRIs. DM should be implemented with sensitivity and adaptability. Emotions can be complex, and the robot's responses should reflect an understanding of human emotions and social cues for various scenarios and user groups [20]. Moreover, ethical guidelines are observed to ensure respectful, responsible interactions with humans. Thus, the robot first extracts GER information, which is processed by the GER component to determine emotion labels. These labels are then classified by a separate classifier component. The GER component communicates the emotion classification back to the robot. Depending on whether the GER result is positive or negative, as shown in Figure 6, the robot either initiates a chatbot interaction with the group or moves away. This diagram illustrates a basic flow of interactions in this context, recognizing that actual implementations may involve more complexity and conditions [21].The action of DM is taken depending on either positive or negative GER labels:

1. Positive GER label initiating the chat box if the GER label for a scene is positive indicates the group's emotions are clear and positive. The robot can initiate a chatbot or engage in a conversation with the group.
2. Negative GER label moving away if the GER label for a scene is negative suggests the group's emotions are diverse or unclear, possibly indicating negative emotions. The robot should consider moving away to avoid potentially negative interactions.

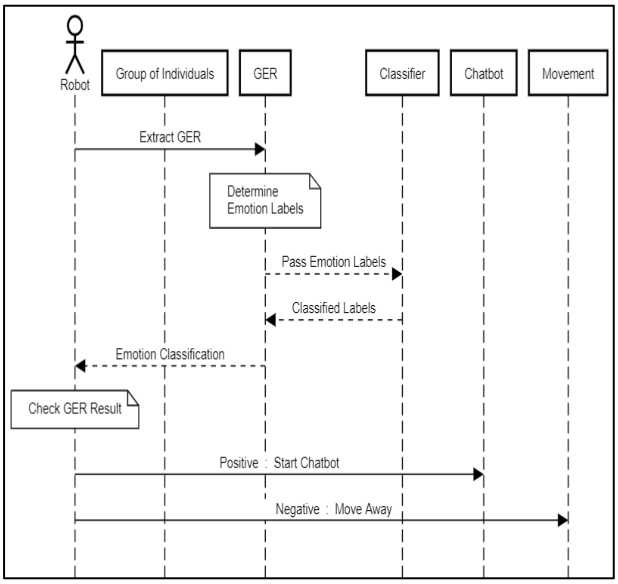

Fig.6 Robot DM

1) DM AND HRI

Within the context of HRI, DM assumes a critical role, particularly in scenarios involving groups of individuals. As humans engage with robots within a collective setting, a multitude of choices and actions are required to navigate the complex dynamics of group interactions [22]. This section explores the field of DM within group contexts, unraveling the underlying cognitive processes, models, and frameworks that shape choices and behaviors. By comprehending the intricacies of DM, the foundation for the development of robots is laid using adaptive, contextually appropriate, and socially sensitive behaviors.

2) COMPLEXITY OF GROUP DM

DM in group contexts is inherently intricate due to the interplay of multiple perspectives, preferences, and objectives. Individuals within a group often possess diverse viewpoints, priorities, and emotional states, leading to a dynamic and sometimes conflicting decision landscape [22]. Group decisions are influenced by social dynamics, power structures, and the desire for consensus [23]. Understanding this complexity is paramount for robots aiming to facilitate and participate in group decision-making processes. The following aspects outline the complexities in group DM:

i. ***Nature of Decision Process*****:**

This process involves multiple perspectives, preferences, objectives, leading to a dynamic, conflicting decision landscape.

ii. ***Diverse Viewpoints***:

Individuals within a group possess diverse viewpoints, priorities, and emotional states, further contributing to complexity.

iii. ***Social Dynamics:***

Group decisions are influenced by social interactions, power structures, and the quest for consensus, adding layers of complexity.

iv. ***Dynamic and Conflicting:***

The interplay of numerous factors makes DM inherently intricate and sometimes marked by conflicting choices.

v. ***Importance of Understanding:***

Complete understanding of this complexity is essential for robots facilitating or participating in group DM.

V. FUTURE WORK, SUGGESTIONS AND CONCLUSION

A. FUTURE WORK SUGGESTIONS

1. Enhanced Emotional Understanding:

Future work can focus on enhancing the system's emotional intelligence by recognizing refined emotions and complex emotional states beyond the basic six.

2. Real-Time Processing Optimization:

Addressing hardware constraints for real-time processing is essential for practical deployment. Optimizing the CNN model and exploring efficient architectures can ensure the system operates seamlessly on resource-constrained robotic platforms.

3. Contextual Understanding:

Future work should aim to enhance the system's contextual understanding of human emotions and social interactions. This process might involve incorporating context-aware algorithms that consider situational factors.

4. Privacy Solutions:

Research can delve into privacy-preserving methods for emotion recognition, addressing concerns related to data security, consent, and user privacy. Developing transparent, accountable practices is essential for user acceptance.

B. CONCLUSIONS

This paper **"Enhancing Human–Robot Interaction through Group Emotion Recognition"** has reached several remarkable conclusions:

1. Dependable Emotion Recognition and DM:

The paper successfully develops a method for emotion recognition, enabling the accurate detection of emotions from individual faces in dynamic HRI scenarios. This method serves as the foundation for group emotion recognition and subsequent DM.

2. GER Calculations:

The proposed method for determining group emotion based on the entropy of distributed emotions and the size of each face in the frame demonstrates the feasibility of understanding collective emotions. By combining proximity metrics and entropy calculations, GER provides valuable insights into the emotional dynamics of groups.

3. Ethical Considerations:

This paper acknowledges the ethical implications of emotion recognition technology, emphasizing the need for responsible use, privacy considerations, and user consent. These ethical concerns are integral to the practical implementation of the system.

REFERENCES

[1] Matteo Spezialetti, "Emotion Recognition for Human-Robot Interaction: Recent Advances and Future Perspectives," Frontiers in Robotics and AI | www.frontiersin.org, 2020.

[2] Zhiqin Zhang, "Deep Face Emotion Recognition," Journal of Physics: Conference Series, 2018.

[3] Felipe Cid, "A real time and robust facial expression recognition and imitation approach for affective human-robot interaction using Gabor filtering," 2014.

[4] "A Novel Multimodal Emotion Recognition Approach for Affective Human Robot Interaction," 2015.

[5] Luefeng Chen, "Softmax regression based deep sparse autoencoder network for facial emotion recognition in human-robot interaction," 2018.

[6] Suhaila N. Mohammed, "Emotion Recognition Based on Texture Analysis of Facial Expressions Using Wavelets Transform," AENSI Publication, 2017.

[7] Luefeng Chen, "Two-layer fuzzy multiple random forest for speech emotion recognition in human-robot interaction," 2020.

[8] Luefeng Chen, "Adaptive Feature Selection-Based AdaBoost-KNN With Direct Optimization for Dynamic Emotion Recognition in Human–Robot Interaction," 2021.

[9] Chiara Filippini, "Improving Human–Robot Interaction by Enhancing NAO Robot Awareness of Human Facial Expression," Sensors MDPI, 2021.

[10] Aitor Toichoa Eyam, "Emotion-Driven Analysis and Control of Human-Robot Interactions in Collaborative Applications," 2021.

[11] Ruth Stock-Homburg, "Survey of Emotions in Human–Robot Interactions: Perspectives from Robotic Psychology on 20 Years of Research," International Journal of Social Robotics (2022) 14:389–411, 2021.

[12] Iro Athina Valagkouti, "Emotion Recognition in Human–Robot Interaction Using the NAO Robot," 2022.

[13] Daniel Octavian Melinte and Luige Vladareanu, "Facial Expressions Recognition for Human–Robot Interaction Using Deep Convolutional Neural Networks with Rectified Adam Optimizer," Sensors MDPI, 2020.

[14] Xianye Ben, "Video-based Facial Micro-Expression Analysis: A Survey of Datasets, Features and Algorithms," IEEE T-PAMI, 2021.

[15] Sigal G. Barsade, "Emotional contagion in organizational life$," © 2018 Elsevier Ltd. All rights reserved. journal homepage: www.elsevier.com/locate/riob, 2018.

[16] Dacher Keltner and Oliver P. John Cameron Anderson, "Emotional Convergence Between People Over Time," Journal of Personality and Social Psychology Copyright 2003 by the American Psychological Association, Inc., 2003.

[17] Noor Kamal Al-Qazzaz, "Complexity and Entropy Analysis to Improve Gender Identification from Emotional-Based EEGs," Journal of Healthcare Engineering / Hindawi, 2021.

[18] Marco Quiroz, "Group Emotion Detection Based on Social Robot Perception," MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations, 2022.

[19] Grazia D'Onofrio, "Emotion Recognizing by a Robotic Solution Initiative (EMOTIVE Project)," Sensors MDPI, 2022.

[20] Xueling Ma, "Group decision-making framework using complex Pythagorean fuzzy information," Neural Computing and Applications, 2020.

[21] Matthew C. Gombolay, "Decision-Making Authority, Team Efficiency and Human Worker Satisfaction in Mixed Human-Robot Teams," Massachusetts Institute of Technology, 2014.

[22] Muhammad Akram, "Group decision-making based on complex spherical fuzzy VIKOR approach," journal homepage: www.elsevier.com/locate/knosys, 2021.

[23] Guilherme Deola Borges, "Decision-Making Framework for Implementing Safer Human-Robot Collaboration Workstations: System Dynamics Modeling," Safty MDPI, 2021.

[24] Xianye Ben, "Video-based Facial Micro-Expression Analysis: A Survey of Datasets, Features and Algorithms," EEE T-PAMI, 2021.