Elderly Motion Analysis to Estimate Emotion: A Systematic Review

Iqbal Hassan* [1],Nazmun Nahid [2], Md Atiqur Rahman Ahad [3], Sozo Inoue [4]
[124]Kyushu Institute of Technology,[3]University of East London

Abstract

This paper presents a systematic review focusing on motion analysis-based emotion estimation in the elderly. Addressing a critical concern, it highlights the challenge of effectively monitoring emotions in older adults and emphasizes the potential development of serious disorders resulting from emotional neglect. The study underscores the importance of emotional well-being in care facilities, where the willingness of elderly individuals to receive care is closely tied to their emotional state. Health practitioners often encounter difficulties when elderly individuals resist care due to emotional dissatisfaction, making monitoring changes in emotional states essential and necessitating comprehensive care records. Through an exhaustive examination of existing literature, the paper suggests that motion-based emotion recognition shows promise in addressing this challenge. Utilizing the PRISMA protocol, the study conducts a qualitative analysis of the impact of motion analysis on emotion estimation. It outlines the current methodologies employed in research and reveals a significant correlation between body motion cues and emotional states in the elderly. Furthermore, it positions motion-based emotion estimation as a viable solution for addressing emotional well-being in older adults and offers guidelines for researchers interested in this area. Based on our study we consider the first review of this kind on motion-based emotion estimation for the elderly, providing insights into potential advancements in addressing emotional well-being in this demographic.

1 Introduction

The global demographic landscape is undergoing rapid aging. In the year 2023, the population of individuals aged 60 years or older reached approximately 1 billion worldwide. Projections indicate a significant increase to

[1]iqbalhassanrakin@gmail.com
[2]nazmun.nahid389@mail.kyutech.jp
[3]mahad@uel.ac.uk
[4]sozo@brain.kyutech.ac.jp

1.4 billion by the year 2030, signifying that one in six individuals globally will be aged 60 years or older at that time. Furthermore, by 2050, the demographic of individuals aged 60 and above is expected to double, reaching a substantial 2.1 billion. Specifically, the population of those aged 80 years or older is anticipated to triple between 2023 and 2050 [1].

As individuals progress through the aging process, they become increasingly susceptible to concurrent health conditions, encompassing mental health disorders such as depression, dementia, and anxiety disorders. Statistical data indicates that approximately 14% of individuals aged 60 and above contend with a mental disorder [2]. Additionally, a myriad of elderly individuals confront challenges associated with diminished mobility, chronic pain, frailty, and various other health issues. Consequently, the provision of healthcare for the elderly emerges as a formidable challenge in societies with an aging demographic. Research underscores the pivotal role of emotions in both physical and mental well-being [5,6]. Regrettably, the expanding elderly population exacerbates the complexity of healthcare workers' task to consistently monitor emotional states. Hence, there arises a critical need to explore automated approaches to address this burgeoning concern.

Emotion estimation constitutes a well-established and extensive area of research with a lengthy history [32–34]. Regrettably, minimal attention has been directed specifically towards the nuanced domain of emotion estimation in the elderly. Numerous challenges emerge when applying conventional emotion estimation approaches to this demographic. Consequently, this paper seeks to elucidate the potential of emotion estimation in older individuals, particularly focusing on motion-based methodologies. To achieve this objective, four research questions have been formulated:

- RQ1: What is the significance of estimating emotions in the elderly population?
- RQ2: What are the key impediments associated with employing prevalent emotion estimation methods for the elderly?
- RQ3: Is there a modality that can effectively address the issues arising from conventional modalities in the context of elderly emotion estimation?
- RQ4: What are the prospective research challenges in this domain, and what strategies can be employed to address them?

Through our research, we have endeavored to systematically address these inquiries by reviewing existing literature and presenting the findings coherently. Additionally, our efforts aim to identify gaps in the current research methodology concerning the experimental approach, conditions of data collection, evaluation methods, and implementation procedures. Furthermore, we offer guidelines for the application of this approach in future research endeavors. The contributions of our study are delineated as follows:

- We underscore the critical importance of accurately estimating emotions in the elderly population and the escalating challenges associated with conventional emotion recognition methods for this demographic.

- We present a comprehensive analysis of existing literature spanning two decades, which supports the proposition that body motion analysis holds significant promise as a superior modality for effective emotion recognition in the elderly.
- We provide a succinct overview of existing motion-based emotion recognition systems and outlines the practical application of this approach for the elderly, accompanied by recommendations for future research directions in this domain.

To achieve these, we highlight that the study adheres to the rigorous PRISMA protocol, ensuring a systematic and robust review of the literature.

Among the 27 papers we have chosen from the initial 499 papers, 15 papers are used for understanding motion based emotional cues. The summary of these papers are shown in Table 1. We have studied 5 review papers to generate the clear scenario of current motion based emotion studies as shown in Table 2. Final to show the state of motion based elderly emotion estimation study we have chosen 7 studies shown in Table 3 In the subsequent sections of this manuscript, we offer concise explanations for these assertions. To the best of our knowledge, this study marks the pioneering effort exclusively concentrating on the estimation of emotions in the elderly through motion analysis.

2 Background

Within this section, we aim to succinctly elucidate the rationale behind undertaking this research. Our exposition will underscore the significance of observing emotional changes within care facilities and outline the challenges associated with the application of prevailing methods of emotion recognition to the elderly.

2.1 Importance of Elderly Emotion Estimation

Emotions encompass affective and valenced responses to meaningful stimuli [11]. Positive emotions entail pleasant or desirable reactions to situations, with evidence suggesting that they contribute to the development of various cognitive resources, enhancing life satisfaction and overall well-being in patients [12]. Within the healthcare context, emotional intelligence assumes a pivotal role [7–10]. This form of social intelligence involves comprehending and responding to the emotional shifts in others [3]. It comprises four key facets: the perception of emotions, emotional assimilation, understanding emotions, and the ability to regulate emotions [4]. Consequently, caregivers must remain cognizant of these aspects while monitoring and attending to the emotional well-being of the elderly during the provision of care.

Research indicates a predominant focus on the examination of negative emotions, driven by the perceived correlation with patient satisfaction [13–15]. However, this emphasis on negativity can impede the development of robust and health-promoting provider-patient relationships.

Sbarra and Coan underscore the centrality of close relationships and social connections to human health [16]. The elderly express that being acknowledged by their caregivers contributes to a sense of hope [17], a factor deemed crucial by patients and influential in fortifying relationships with healthcare providers [18]. Therefore, the comprehensive observation of emotional changes holds paramount importance within care facilities. Regrettably, the demanding nature of caregiver responsibilities renders continuous monitoring of emotional variations in elderly patients unfeasible, potentially leading to severe disorders such as depression and anxiety [52]. Consequently, a meticulous estimation of elderly emotions emerges as a critical imperative.

2.2 Elderly Emotion Estimation: Current State and Challenges

The proportion of older individuals residing in long-term care facilities is comparatively modest, varying from 1% to 3% within the age bracket of 65 to 84 years. However, this percentage experiences a notable escalation, reaching 9%, among individuals aged 85 and above [28]. In contrast, it is estimated that approximately 35% of individuals will, at some point in their lives, undergo a period of residence in a nursing home setting [29].

Despite the significance of emotion recognition for the elderly, datasets explicitly designed for this purpose are notably scarce. Many datasets encompass a broad spectrum of age variations to enhance their robustness [30]. However, models trained on such datasets often exhibit suboptimal performance when applied to the elderly [42–44]. Several studies also highlight age-related challenges in recognizing emotions such as fear [23, 25–27], disgust [22], and occasionally happiness [22, 26]. Based on our investigation, the challenges associated with Elderly Emotion Estimation can be summarized as follows:

- Insufficiency of datasets exclusively focused on the elderly [42].
- Alterations in the ability to express and recognize emotions through facial expressions due to aging-related factors such as facial skeleton atrophy, soft tissue loss, and altered muscle positioning [19].
- Impediments in facial expression due to factors like wrinkles, folds, and muscular wear in older individuals [20, 21].
- Vocal expression studies indicate less accurate recognition of anger and sadness in older adults compared to their younger counterparts [22–25].
- Challenges in adapting to wearable devices among the elderly [45], despite their necessity for collecting physiological signals.
- Variability in gait speed with aging [46].
- Age-related limitations in mobility, with approximately 35% of individuals aged 70 and a majority of those over 85 experiencing limited mobility [47].

Collectively, these challenges render the estimation of emotions in the elderly an exceptionally formidable domain.

2.3 Paper Scope and Objective

Ray Birdwhistell's research findings, as presented in his study, indicate that during face-to-face interactions, 35% of emotion is communicated through verbal cues, while the remaining 65% is conveyed through non-verbal signals [48]. A comprehensive review of the literature, spanning two decades and encompassing both psychological analyses and experimental approaches, reveals that approximately 95% of emotion recognition studies are predominantly centered around facial expressions [49]. In our examination of this extensive body of literature [49–58], we note that roughly 80% of the studies provide evidence supporting the notion that body movement has the potential to surpass face-based emotion recognition. The remaining 20% contend that body motion is not lacking in emotional cues compared to facial expressions. Several factors contribute to this observation:

- The larger surface area and higher degrees of freedom associated with the body [59, 60].
- Unlike other modalities, gait and other body movements conveying emotional cues allow subjects to maintain a relative distance from the camera [59, 60].
- Motion analysis enables the estimation of both the nature and intensity of emotions [61].
- Studies based on motion require less cooperation from subjects [51].
- Motion data closely mirrors real-life scenarios, requiring minimal to no interference in the data collection process [51].

In the past, the processing and analysis of motion data presented challenges attributed to technical limitations. However, with the progress in gait analysis, marker-less pose analysis, and gesture analysis, motion-based emotion recognition is experiencing a swift surge in popularity. It has emerged as a contemporary focal point, lauded for its promising efficacy in both individual and group-based emotion estimation [62].

3 Review Method

Within this section, we concisely elucidate the processes of generating keyword strings, conducting literature exploration, establishing inclusion and exclusion criteria, and delineating the survey protocol. The survey is outlined as follows:

- Timeline: 2004 $\sim$ 2024 as shown in Figure 2.
- Protocol: Adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [63].
- Initial Paper Count: 499.
- Final Paper Count: 27 [32–41, 50–53, 65, 67, 69–79].

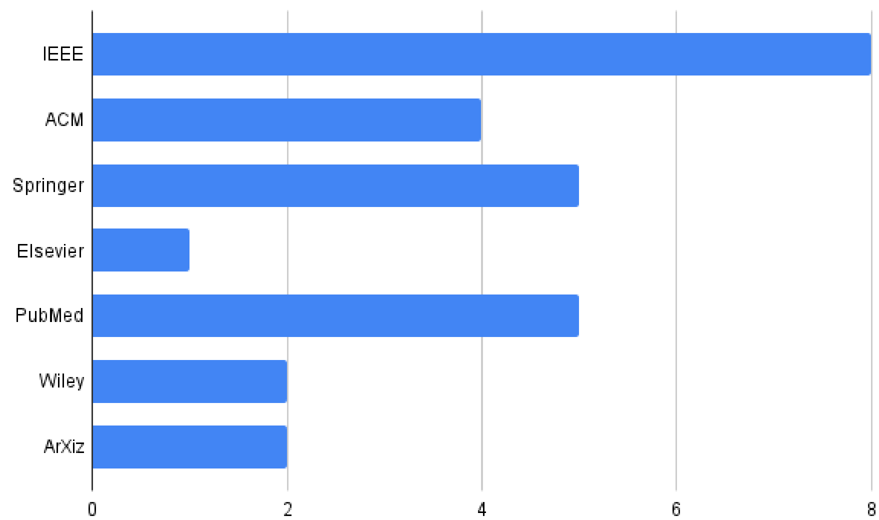

Figure 1: Statistics of all the collected articles' based on publishers.

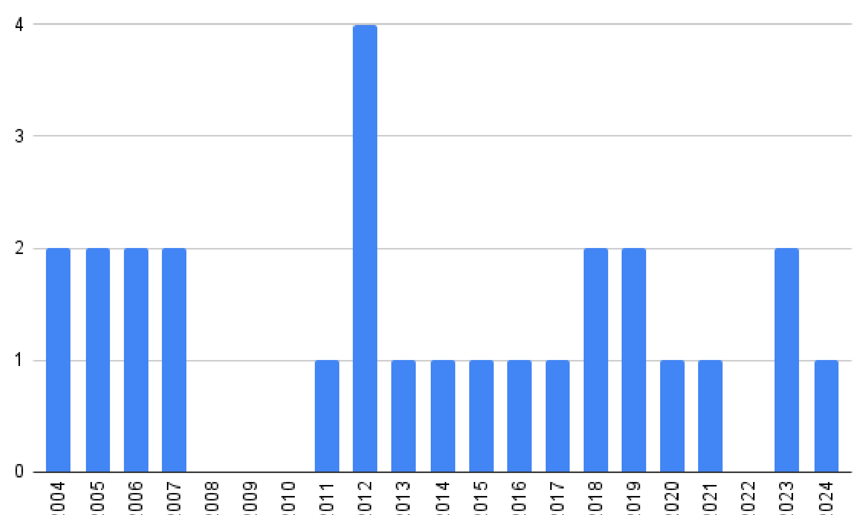

Figure 2: Statistics of the collected articles' distribution by the publication year.

3.1 Keyword Search

The initial phase of the review involves the formulation of keywords. A comprehensive examination of research and reviews pertaining to the estimation of emotions in the elderly has been conducted to identify existing research gaps. Additionally, interviews with caregivers from various care facilities have been undertaken. Synthesizing insights from both the study and interviews, the definitive set of keywords for the search process has been derived, as outlined below:

- First String: (Elderly emotion estimation OR recognition OR prediction OR emotion analysis) OR (How to identify OR predict OR estimate OR recognize OR assess elderly emotion)
- Second String: ((Motion OR Gait OR Pose) to emotion) OR ((Walking OR Daily activity OR Sitting OR Eating) AND Emotion)
- Third String: (Nurse patient emotion) OR (Assistance emotion) OR (Care emotion)
- Fourth String: (Emotion dataset) OR (Devices for emotion estimation)

The ultimate search string is crafted by amalgamating the four designated strings. Following the formulation of this comprehensive string, searches are conducted across the repositories of the ACM Digital Library, Science Direct, IEEE Xplore, Scopus, Web of Science, and PubMed. Additionally, searches are extended to encompass the Google Scholar and ResearchGate platforms. The statistics of the final amount of paper kept for review is shown in Figure 1.

3.2 PRISMA

Our study adheres to the guidelines provided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [63], as illustrated in Figure 3. Aligned with our research questions and overarching objectives, we establish our inclusion and exclusion criteria.

Exclusion Criteria:

- Articles composed in languages other than English.
- Exclusion of books, errata, editorials, and proceedings.
- Elimination of papers that do not address human emotion.
- Exclusion of papers specifically addressing caregiver emotion.
- Disregard for papers concentrating on robot integration or applications unrelated to emotion recognition.
- Omission of papers associated with the decline in emotion perception in the elderly.
- Exclusion of review papers lacking any motion-based emotion estimation approach.

Inclusion Criteria:

- Articles encompassing activities related to emotion estimation applications.

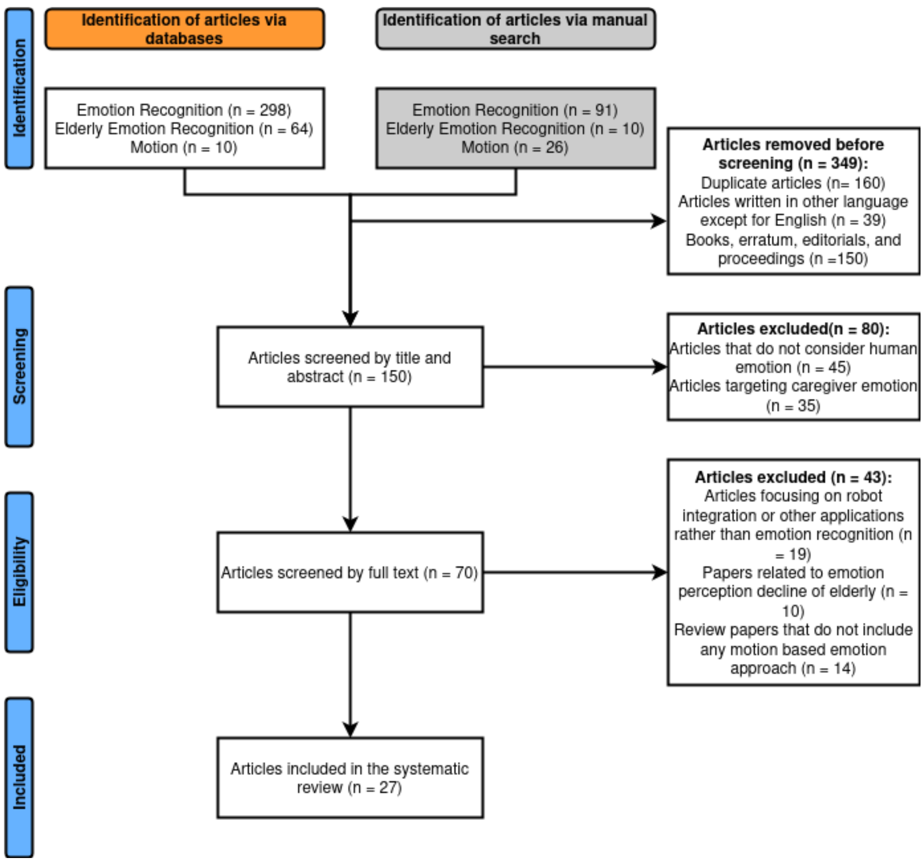

Figure 3: PRISMA flow diagram illustrating the systematic review protocol.

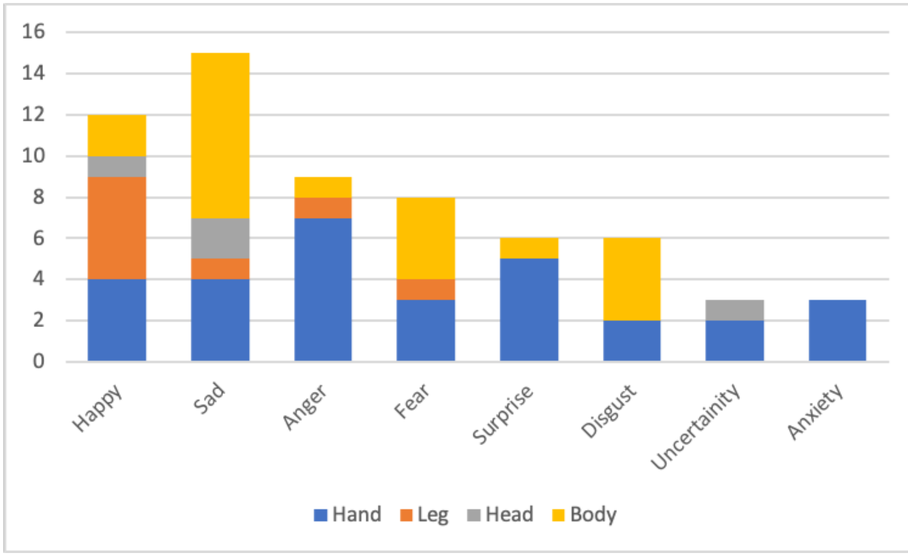

Figure 4: Distribution of different body parts activation level for specific emotional states.

- Papers explicitly delineating challenges associated with analyzing emotions in the elderly.
- Papers clearly articulating a focus on motion-based emotion estimation in their subjects.
- Papers detailing motion-based emotion datasets that specifically involve the elderly age group.
- Papers presenting comparisons between motion-based approaches and other modalities.
- Articles providing comprehensive overviews of motion-based emotion recognition.
- Papers explicitly referencing behavioral cues derived from motion for emotion analysis.

4 Motion to Emotion Estimation

Motion-based emotion estimation entails the systematic analysis and interpretation of human movements, encompassing elements such as gait, posture, gestures, and overall body motion [66,68]. The objective is to deduce or evaluate an individual's emotional state through these observed movements. The primary aim of motion-based emotion estimation and recognition is to capture, scrutinize, and interpret patterns within body movements that signify distinct emotional states. It is noteworthy that while certain studies include lip movement, eyebrow movement, and eyelid movement in the realm of motion, we specifically exclude them as they are categorized under facial action units [64].

4.1 Motion Based Emotional Cues

Multiple investigations have affirmed that body language, encompassing gait and postural characteristics, serves as a repository of emotional cues. Distinct emotional states manifest in varied kinematic patterns. Drawing upon the findings of previous studies [32–41, 65, 67, 69–71], we delineate alterations in body movement corresponding to specific emotions, as detailed in Table 1 and in Figure 4.

Table 1: Popular body motion cues for respective emotions [32–41, 65, 67, 69–71]

Emotions	Body Motion Cues
Happy	Arms open Legs parallel Looking around Increased gait speed Arms move Legs stretched apart Body extended Arm swing Legs open Feet pointing Hands kept high Increased step length
Sad	Body dropped Body shifted Body parts covered Hands kept lower Reduced gait speed Shrunk body Trunk leaning forward Arms around the body Moving slowly Reduced step length Bowed shoulders Face covered withhands Hands over the head Head bent Reduced reaction time

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Table 1: Popular body motion cues for respective emotions [32–41, 65, 67, 69–71] (Continued)

Anger	Body spread Lift one hand up Arms crossing Hands on hips or waist Finger point Increased thigh elevation angle Clenched fists Finger or hand shaky Increased arm swing
Fear	Muscle tension Elbows dragged inward Hands try to cover body Legs and arms crossing Body contracted Increased cadence Hands or arms clenched Body backing Increased postural tension
Surprise	Abrupt backward movement Hand touch head Hand move toward the head Head shaking Hand touch face or mouth Hand cover cheek or mouth
Disgust	Backing Orientation changed Hand cover neck Move to a side Body shifted Hand on mouth
Uncertainty	Shoulder shrug Palms up Shake head side by side
Anxiety	Hand close and flex Fingers moving Fingers tapping

This observation reveals that distinct body parts are notably engaged, particularly in the case of prominent emotions.

4.2 Motion to Emotion: A Brief Overview

In motion-based emotion analysis, two primary types of emotional models prevail: continuous and categorical. A diverse array of features can be employed for this purpose, encompassing both handcrafted features and, owing to the advancements in neural networks, various learning-based features. The applicability extends to both classical machine learning and deep learning methodologies, given that motion data is sourced not only from cameras but also from devices such as Kinect. A summary of the current landscape is provided in Table 2 and Figure 5, informed by the insights gleaned from the previously conducted review studies [50–53, 72]. Here we have only mentioned the contactless methods as body worn sensors may arise discomfort for elderly.

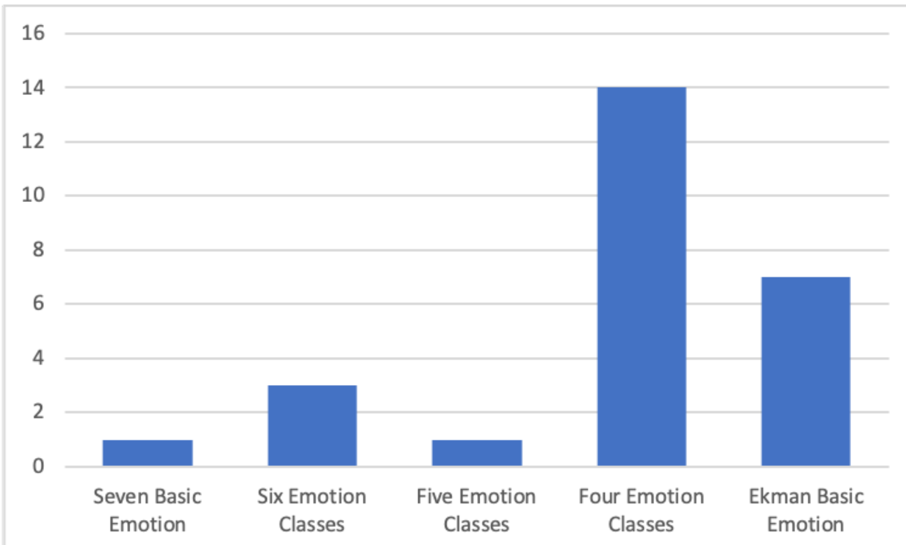

Figure 5: Distribution of various emotional models in the collected articles.

Within the domain of motion-based emotion analysis, diverse categories of features merit consideration, with particular emphasis on motion-based features that are distinct and not accessible in other modalities.

5 Elderly Emotion from Motion: Current Landscape and Outlook

In this section, we have delineated the existing landscape of research on body motion analysis for elderly emotion, elucidated the challenges inherent in this domain, and provided directions towards potential solutions for overcoming these challenges.

5.1 Current State of Research

In recent times, the growing fascination with the motion-to-emotion phenomenon has resulted in an increased popularity, accompanied by the widespread adoption of statistical, machine learning, and deep learning methodologies for constructing robust frameworks. The current state of

Table 2: A brief overview of the motion-to-emotion estimation based on the currently available literature study

Emotion Models	Continuous	Categorical
	Seven Basic Emotions Six Emotion Classes Five Emotion Classes Four Emotion Classes Ekman Basic Emotion	Valence/Arousal Dimension Componencial Model
Features	Hand Crafted	Learned
	PCA LBP HOG Gabor Filter Fourier transformation Wavelet Transformation PSD DWT LDA Center of Pressure (COP) Kinematics Fluidity Skewness Kurtosis Min-Max Analysis Binary Connected Component Operator Postural Geometric	CNN Gamma GWR Network ST-ConvPose Gray Level Information
Classification	Classical Machine Learning	Deep Learning
	SVM RF KNN GMM BBN BayesNet Hidden Naive Bayes Ensemble tree LR	LSTM CNN FFNN GCNN FDCNN ConvLSTM Recurrent GWR Network Resnet50
Hardware	RGB Camera MOCAP RGB-D Camera(i.e. Kinect, RealSense) Depth Sensor	

Table 3: List of available datasets for elderly emotion estimation considering motion

Dataset	Age	Gender	Profession	Stimuli	Special Condition
FABO [73]	18-50	Male (11) Female (12)	N/A	None	None
Private DB [74]	24-60	Male (8) Female (4)	Actor	Game	None
Private DB [75]	22-65	Male (60%) Female (40%)	• Student • Professional	None	None
Private DB [76]	55-80	Female (6)	• Patient • Normal	Image	PD
SEMAINE [77]	22-60	Male (38%) Female (62%	N/A	SAL	None
EMPATHIC [78]	65+	Male (52) Female (105)	N/A	Game	None
ElderReact [79]	65+	Male (20) Female (26)	N/A	Video	None

research, encapsulated in Table 2, reflects the prevailing approaches for estimating emotional states based on body motion. Despite the heightened attention given to the motion-to-emotion paradigm, a noticeable gap exists in its application to the elderly demographic. The existing body of research aimed at unraveling the connection between motion and emotions among the elderly is notably scarce. Our extensive survey reveals a predominant focus on the younger demographic in current studies, with elderly subjects, if included, often comprising only a subset within a larger participant pool. As a result, these studies fall short in providing substantial insights into the intricacies of the motion-to-emotion spectrum tailored specifically to the parameters relevant to the elderly. The scarcity of specialized investigations in this domain underscores the necessity for targeted research efforts. Table 3 concisely outlines the currently available benchmark datasets for emotion estimation derived from body motion, highlighting a discernible emphasis on datasets with a specific focus on the elderly population.

5.2 Key Challenges

Despite the potential superiority and rapid popularity gain of motion-based emotion studies, certain challenges persist. To effectively implement such systems in a facility, it is imperative to tackle these issues. The following portion of the literature shades some light on this topic.

5.2.1 Data Unavailability

According to our survey, merely 28.57% of the dataset was explicitly designed with the elderly in consideration. This design choice is primarily driven by the aim to enhance dataset robustness, which is a commendable strategy when seeking insights into emotions across a diverse age range. However, for scenarios where the exclusive focus is on the elderly demographic, this approach exhibits significant limitations. The rationale behind this limitation lies in the fact that numerous behavioral cues undergo alterations with the aging process [42].

5.2.2 Ethical Concerns

Significant challenges in vision-based methodologies revolve around privacy and security considerations. The deployment of technology for gait and posture analysis introduces notable privacy concerns. Ensuring the ethical adherence of data collection and analysis becomes paramount, particularly when dealing with vulnerable populations.

5.2.3 Mobility Limitations

The decline in muscle strength, joint flexibility, and balance associated with aging can notably impact both gait and posture [47]. Such age-related changes have the potential to influence the overall expressiveness of movement.

5.2.4 Gait Speed Decrease

Certain emotions exhibit high dynamics but lack the ability to induce rapid changes in gait and posture [46]. Capturing such dynamic emotions poses a significant challenge.

5.3 Potential Solutions and Future Directions

In response to these challenges, we have proffered solutions grounded in our observations.

5.3.1 Collect Dedicated Data Set for Elderly

To address challenges related to data, the following measures may be undertaken:

- Proactively seek and include a more substantial representation of elderly participants in the dataset. This can be achieved through targeted recruitment initiatives, collaboration with care facilities, retirement communities, or hospitals. Ensure precise annotation of emotional expressions demonstrated by elderly individuals.

- Ensure accurate annotation of emotional expressions displayed by elderly individuals by devising customized labels that capture the nuances and variations in emotional cues specific to the aging population.
- Tailor scenarios or situations in the dataset to be more relevant to the daily lives of elderly individuals. Consider incorporating scenarios reflective of their living conditions, social interactions, and common activities.
- Engage in collaboration with experts in gerontology and psychology to gain a deeper understanding and integration of age-specific emotional expressions. Such collaboration can offer valuable insights into the distinct emotional dynamics of the elderly population.

5.3.2 Data Anonymization

To address ethical concerns, the following measures can be implemented:

- Deploy robust anonymization and de-identification techniques to eliminate personally identifiable information from the collected data. This ensures the protection of privacy, particularly for vulnerable populations, throughout the analysis.
- Utilize encryption protocols for data transmission to prevent unauthorized access during the transfer process. This is essential for safeguarding sensitive information and preserving the confidentiality of gait and posture data.
- Establish and adhere to time-bound data retention policies, ensuring the deletion or anonymization of data after a predefined period. This minimizes the risk of prolonged exposure and unauthorized access.

5.3.3 Generate Model Based on Partial Body Parts

- Regarding Dataset [79], XGBoost emerges as the optimal model for all emotions except fear, with SVM exhibiting performance closely aligned with XGBoost across all emotions. The comparatively lower performance of Naive Bayes is anticipated, given its assumption of independence among predictors.
- In the case of Dataset [78], emphasis was placed on extensive feature engineering, particularly concentrating on head movement.
- Both of these investigations underwent reannotation involving the elderly to ensure the accurate perception of labels.

5.3.4 Utilize Features Not Related to Velocity

- Examining Table 1 reveals the presence of various features, even in the absence of velocity features. We can concentrate on and integrate the methodologies outlined in Table 2.
- Analysis of Figure 4 indicates that different body parts hold varying significance for each emotion. Hence, efforts can be directed towards highlighting prominent parts, such as the hand.

- Both of these investigations underwent reannotation involving the elderly to ensure the accurate perception of labels.

6 Conclusion

In this paper, we have systematically review the current literature on elderly emotion estimation, show the limitations of the existing research and finally give insight on how motion can be a better approach for elderly emotion estimation. The increasing aging of the global population necessitates a thorough reassessment of healthcare strategies, emphasizing the emotional well-being of the elderly. The rise in the number of individuals aged 60 and above corresponds with an increasing prevalence of mental health conditions within this demographic. This paper has delved into the significance of Emotional Intelligence (EI) in the context of elderly healthcare, emphasizing its crucial role in comprehending and addressing the emotional changes encountered by the aging population. Despite the recognized importance of emotion in overall health, the increasing elderly population poses a significant challenge for healthcare professionals in maintaining consistent monitoring of emotional well-being. This research delves into the realm of emotion estimation, revealing a noteworthy gap in research specifically tailored for the elderly. Through a thorough analysis of prevalent emotion estimation approaches, the paper identifies and clarifies the distinct challenges associated with applying these methods to the elderly demographic. This research goes beyond merely identifying challenges; it offers a roadmap for bridging the gaps.

Through underscoring the significance of elderly emotion estimation, scrutinizing the heightened intricacies of emotion recognition in the elderly, assessing prevailing emotion analysis methods, and suggesting the viability of leveraging body motion for emotion recognition, the paper contributes valuable insights to the trajectory of elderly healthcare. The outlined survey of motion-based emotion recognition systems establishes a groundwork for subsequent research and implementation endeavors. Executed in accordance with the PRISMA protocol, this investigation acts as a catalyst propelling continuous endeavors to improve emotional care for the expanding elderly demographic. The outlined strategies and recommendations establish a trajectory for future research pursuits, with the objective of crafting and introducing innovative solutions that prioritize the emotional well-being of the elderly within an progressively aging society.

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