Sensors and Materials, Vol. 38, No. 8 (2026) 4399–4414
MYU Tokyo

S & M 4573

Feasibility of Eulerian Video Magnification for Noncontact Heart Rate Monitoring in Older Adults with Dementia

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(Received May 20, 2026; accepted June 23, 2026)

Keywords: older adults with dementia, horticultural therapy, noncontact heart rate monitoring, Eulerian video magnification, region of interest, electrocardiography

In response to the increasing demand for noninvasive physiological monitoring in dementia care, particularly with horticultural therapy, in this study, we evaluated the feasibility of Eulerian video magnification (EVM) for contact-free heart rate estimation. Utilizing dorsal hand imagery from older adults with dementia, we compared two region-of-interest (ROI) selection strategies against electrocardiography (ECG) benchmarks. Empirical results indicated that the large-area ROI strategy outperformed the small-area alternative, yielding a lower mean absolute error of 9.00 bpm and a stronger correlation trend with ECG data ($\rho = 0.516$, $p = 0.059$). This performance advantage is primarily due to the spatial averaging effect, which effectively mitigates noise from skin heterogeneity, specular reflections, and microtremors characteristic of this demographic. Overall, integrating EVM with dorsal hand imaging demonstrates preliminary feasibility for clinical monitoring. Future research should prioritize expanding cohort sizes and validating signal robustness within dynamic horticultural environments to ensure practical therapeutic utility.

1. Introduction

Against the background of rapid population aging, dementia has become a major factor contributing to functional decline, reduced ability to perform activities of daily living, and increased demand for long-term care among older adults. Horticultural activities provide

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https://doi.org/10.18494/SAM6444

ISSN 0914-4935
https://myukk.org/

multisensory stimulation, naturalistic contexts, relatively low risk, and opportunities to sustain participation motivation and social interaction. Consequently, they have increasingly been applied as nonpharmacological interventions for older adults with dementia to promote daily functioning and support psychological health. However, when evaluating the intervention effects of horticultural therapy in older adults with dementia, reliance solely on subjective observation or conventional clinical scales often fails to capture physiological changes during the activity process in a timely and fine-grained manner. Therefore, establishing an assessment tool that is objective, low burden, minimally intrusive, and suitable for long-term monitoring has become an important issue in horticultural therapy research and gerontechnology development.(1–3)

At present, the outcomes of horticultural therapy are commonly assessed using clinical scales, behavioral observations, and contact-based physiological sensors. Although clinical scales can provide information regarding overall functional status, quality of life, and psychological or behavioral performance, their sensitivity and temporal resolution remain relatively limited for detecting subtle physiological or emotional changes induced by short-term interventions.(4) In contrast, contact-based physiological sensors can provide more objective physiological indicators, such as heart rate, blood oxygen saturation, and electrodermal activity. However, their operation typically requires electrodes, wires, or wearable devices to be attached to the participant's body. For older adults with dementia who experience cognitive decline, sensory sensitivity, or resistance-related behaviors, such devices may induce stress responses, behavioral interference, or physiological resistance, thereby affecting the participant's natural activity state.(5) In addition, excessive reliance on wearable or contact-based devices may cause participants to deviate from their original behavioral patterns, reduce the naturalness and ecological validity of horticultural activity contexts, and subsequently affect both the accuracy of intervention outcome assessment and the participant experience.(6)

With the growing demand for telemedicine, smart care, and long-term health monitoring, noncontact heart rate monitoring (NHRM) has gradually become an important direction in clinical physiological sensing and gerontechnology.(7) Compared with conventional contact-based sensing methods, NHRM can acquire and analyze physiological rhythm variations through imaging or optical signals without directly contacting the skin or interfering with participant activities. This characteristic not only helps reduce skin irritation, discomfort associated with device wearing, and operational errors, but also lowers the risk of cross-infection. Moreover, it enables physiologically meaningful information to be obtained while maintaining participants' natural behavior and psychological comfort.(8–10)

Traditional noncontact physiological measurement methods mainly rely on remote photoplethysmography (rPPG). The basic principle of rPPG is to estimate physiological features, such as heart rate, by capturing weak skin-color amplitude variations caused by periodic changes in microvascular blood volume within facial regions, such as the forehead or cheeks.(11) However, the measurement performance of rPPG is highly dependent on the signal-to-noise ratio (SNR) of the target region and the quality of the acquired images.(12) In the context of this study, the measurement site was shifted from the face, which contains dense vascular distributions and is commonly used in rPPG analysis, to the dorsal hand region, where physiological signals are weaker. Although this shift helps reduce privacy concerns and psychological stress associated with facial imaging, it also increases the difficulty of signal extraction. In particular, for older adults with dementia, age-related skin aging may alter optical scattering, absorption characteristics, and surface reflectance, making the original physiological signals more susceptible to interference from ambient illumination, local reflection, and background noise.(13) Such signal attenuation and noise contamination not only reduce the robustness of physiological feature extraction but also highlight the limitations of conventional rPPG when applied to clinically complex contexts and nonfacial monitoring regions.

To overcome these limitations, we investigated the feasibility of applying Eulerian video magnification (EVM) to NHRM in older adults with dementia.(14) EVM primarily amplifies weak color variations or subpixel motion within specific frequency bands through spatial decomposition and temporal filtering of image sequences, allowing subtle physiological rhythms that are difficult to observe with the naked eye to be enhanced and analyzed.(15,16) Theoretically, if weak optical variations related to cardiovascular pulsation remain present in the dorsal hand region, EVM may improve their observability through signal enhancement and thereby serve as a technical basis for low-contact or noncontact physiological monitoring. Compared with rPPG methods that rely solely on color variations in raw images, EVM can enhance subtle image variations and may therefore be more suitable for older adult care settings characterized by low signal intensity, limited participant cooperation, or the need to preserve a natural activity context.

If EVM demonstrates satisfactory consistency, accuracy, and stability in horticultural activity contexts involving older adults with dementia, it may help compensate for the limitations of conventional intervention assessment methods in terms of objectivity and immediacy. More importantly, this technique may establish a physiological feedback mechanism with ecological validity while avoiding excessive interference with participants' natural behaviors. Researchers would thus be able to acquire more continuous and quantitatively meaningful physiological response data during the activity process. This approach may serve not only as an auxiliary tool for evaluating the effectiveness of horticultural therapy but also as a potential method for applications in geriatric care, rehabilitation activities, nonpharmacological intervention assessment, and smart health monitoring.

Nevertheless, applying EVM to clinical and care contexts involving older adults with dementia still presents several technical challenges. Age-related skin aging, differences in local vascular distribution, nonuniform optical reflection over the dorsal hand, variations in ambient illumination, and micromotion artifacts during activity may all reduce the SNR of physiological signals and further affect the stability and reliability of heart rate estimation.(17) In addition, horticultural activities are inherently dynamic and involve hand manipulation, postural adjustment, tool use, and plant interaction, all of which may increase nonphysiological variations in the image. Therefore, NHRM in such contexts requires not only validation of the ability of EVM to amplify weak physiological signals but also further evaluation of how different region-of-interest (ROI) selection strategies affect noise suppression, motion interference reduction, and estimation stability.

On the basis of the above background and research gaps, the primary objective of this study was to investigate the feasibility of applying EVM to NHRM for supporting horticultural therapy assessment in older adults with dementia. Because case recruitment is highly challenging, we did not focus on before-and-after differences induced by horticultural therapy. Instead, we focused on the feasibility of NHRM. Specifically, we aimed to achieve three objectives. To make the notion of feasibility verifiable, we defined explicit, externally anchored feasibility criteria *a priori* and treated feasibility as a staged construct, separating baseline accuracy under controlled conditions from robustness under real-world activity conditions (Sect. 2.5). First, we sought to verify the accuracy and stability of EVM-based heart rate estimation from dorsal hand images of older adults with dementia in a high-dynamic horticultural therapy context. Second, we systematically analyzed the ability of different dorsal hand ROI selection strategies to suppress environmental noise, physiological interference, and micromotion artifacts, and evaluated their effects on the robustness of heart rate estimation. Third, we assessed the practical value of this technique in improving the ecological validity and quantitative assessment capability of horticultural therapy research. Through these analyses, we aimed to establish a physiological measurement method that is minimally intrusive, objective, and clinically feasible, thereby providing a technical foundation for evaluating horticultural therapy outcomes and developing smart care applications for older adults with dementia.

2. Methods

2.1 Study design and participants

We conducted a feasibility analysis of applying EVM to heart rate estimation in older adults with dementia, using the noncontact heart rate measurement module from an existing participant dataset. A total of 16 older adults with dementia were recruited, including five men and 11 women, with a mean age of 87.9 years. During data collection and verification, two participants were excluded because of unavoidable physiological and health-related factors. Therefore, 14 valid participants were ultimately included in the EVM-based heart rate estimation analysis. All participants were recruited from a study site established in collaboration with Kaohsiung Municipal Kai-Syuan Psychiatric Hospital, and data collection was completed in accordance with the existing institutional review board requirements and informed consent procedures.

Our purpose was not to directly evaluate the intervention effects of horticultural therapy. Instead, we focused on establishing an engineering-based physiological measurement method that can support horticultural therapy assessment. In other words, the main objective was to verify whether EVM combined with dorsal hand imaging is feasible as a low-burden and minimally intrusive heart rate monitoring tool. Although the present measurements were not conducted during actual horticultural activities, the methodological significance of this design lies in first establishing the baseline capability of image-based heart rate estimation in a controlled environment, thereby providing a technical foundation for future implementation in horticultural therapy or geriatric care activity settings. Our study design helped reduce external confounding factors, such as ambient illumination, body posture, and activity-related interference, during the initial validation phase and enabled a more interpretable comparison between the EVM method and electrocardiography (ECG) reference measurements.

2.2 Experimental environment and equipment configuration

In this study, a highly consistent controlled optical environment was successfully established by integrating a standardized dark-box system with an omnidirectional ring light source. This configuration empirically suppressed interference from ambient stray light and nonstationary shadows during image-based physiological signal acquisition. Dorsal hand images were acquired from a top-down view at a nominal distance of 40 cm. A high-resolution image acquisition setting of 1920 × 1080 pixels and a spatiotemporal sampling specification of 30 frames/s were used to ensure sufficient sampling precision for weak blood-flow pulsation signals in both spatial and temporal dimensions, as shown in Fig. 1. In addition, a contact-based ECG system with a high sampling frequency of 1000 Hz was used as the physiological gold standard. This established a high-temporal-resolution reference for the rigorous validation of the accuracy and error characteristics of the noncontact heart rate estimation algorithm.

Furthermore, to address signal synchronization between noncontact image acquisition and the contact-based ECG gold standard, a computer system clock was used to perform strict time-stamp alignment. This ensured consistency between the two physiological data channels for time-domain comparison, which serves as the foundation for the subsequent processing pipeline shown in Fig. 2.

The dorsal hand was selected as the imaging region mainly because of research ethics, participant comfort, and future clinical applicability. For older adults with dementia, facial imaging may raise privacy concerns, induce psychological stress, or cause discomfort, thereby affecting participant cooperation and natural behavioral expression. In contrast, dorsal hand imaging involves fewer facial identification and personal privacy concerns. Moreover, because the hands are the primary body parts involved in horticultural activities, they have potential applicability for future monitoring during activity processes. Therefore, in this study, we used the dorsal hand as the primary imaging region to evaluate its feasibility as a minimally intrusive physiological monitoring interface.

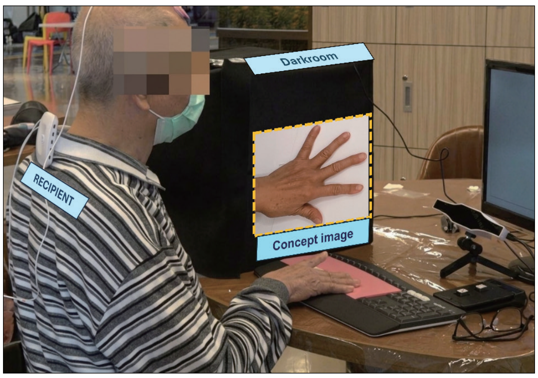


Fig. 1. (Color online) Experimental setup and synchronized measurement system.

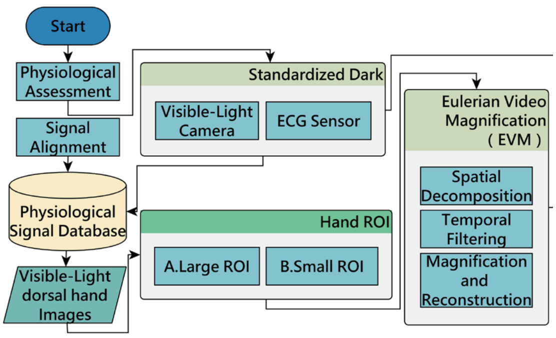


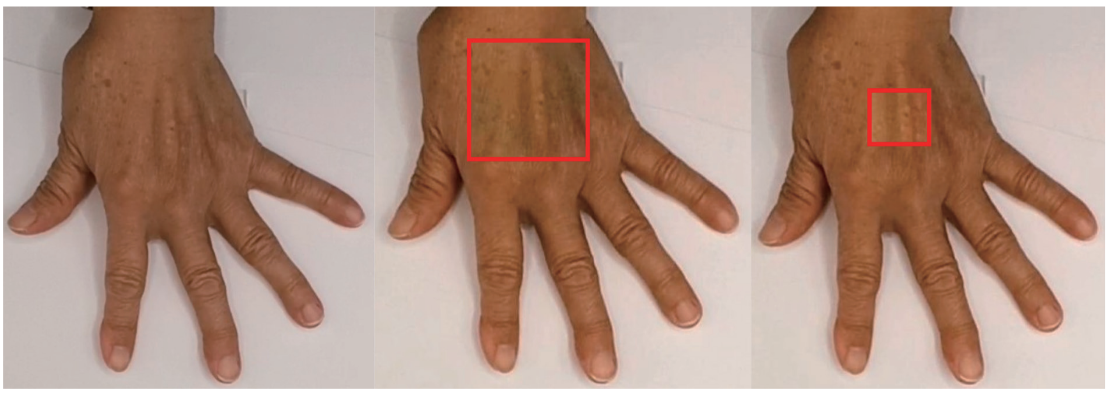
Fig. 2. (Color online) Overview of the signal processing pipeline.

2.3 ROI selection strategies for dorsal hand images

To analyze the effects of different ROI sizes in dorsal hand images on heart rate estimation performance, we designed two ROI selection strategies: a large-area ROI and a small-area ROI. The ROI definition was not based on a static specification with fixed pixel dimensions. Instead, a selection criterion based on signal quality maximization was established. Specifically, the ROI was preferentially selected to include a structurally complete dorsal hand region and part of the forearm, while areas with obvious pigmentation, such as dark spots commonly observed in older adults, and regions with strong local reflection were strictly avoided during ROI selection. This dynamic selection mechanism was designed to exclude sources of variation that may introduce nonphysiological spatial noise, thereby ensuring that representative blood-flow pulsation features could be stably extracted during subsequent spatial decomposition. Figure 3(a) shows the original dorsal hand image used in this study. The image was acquired from above using a visible-light camera in the standardized dark-box environment, while ECG-measured heart rate values were synchronously recorded as the reference standard. Figure 3(b) shows the large-area ROI selection method, which covered most of the visible dorsal hand region and included more information related to blood vessels, tendons, skin texture, and local color variations. Figure 3(c) shows the small-area ROI selection method, which mainly focused on a relatively flat and localized area in the central dorsal hand region to avoid interference from prominent large vessels, hand edges, and highly reflective areas during signal acquisition.

2.4 EVM-based heart rate estimation and comparison with ECG reference measurements

Following the color-amplification formulation,[14] the pipeline was implemented in MATLAB using the matlabPyrTools function and applied to the empirically selected dorsal hand ROI (Sect. 2.3) rather than the full 1920 × 1080 frame. The green (G) channel of the RGB video, which carries the strongest photoplethysmographic content, served as the source signal and was normalized to [0, 1] before processing. Each ROI frame was decomposed with a 4-level Gaussian pyramid. The resulting intensity time series were filtered with an ideal (zero-phase, frequency-



(a) (b) (c)

Fig. 3. (Color online) ROI selection strategies for dorsal hand images: (a) original dorsal hand image, (b) selected large-area ROI, and (c) selected small-area ROI.

domain) band-pass filter with cutoffs of 0.83 and 1.83 Hz, i.e., a heart-rate passband of 50–110 beats/min; as an ideal filter realized through a frequency-domain mask, it has no recursive order. The band-passed signal was amplified by a factor α = 10000 (with secondary channels scaled by an additional attenuation factor of 2) and added back before reconstruction. For each frame, the magnified ROI was reduced to a single value by spatial averaging over all ROI pixels, yielding a one-dimensional pulsation signal. Heart rate was then derived in the time domain by peak detection on this signal, with the minimum peak-to-peak interval set to the cardiac period at 150 beats/min (0.4 s) to reject spurious peaks, and computed as the number of detected peaks divided by the analyzed duration (in seconds), multiplied by 60. In this study, the heart rate measured by ECG was used as the reference standard, and the image signals extracted from dorsal hand videos after EVM processing were converted into heart rate estimates. The basic concept of EVM is to perform spatial decomposition and temporal filtering on image sequences and then amplify specific frequency-band signals associated with cardiovascular pulsation. This process enhances subtle color variations or minute displacements in the dorsal hand region, which are originally weak and difficult to observe. After EVM processing, heart rate estimates were obtained separately from the large-area ROI and the small-area ROI and were compared with the ECG reference values.

The analytical indicators in this study included the mean, standard deviation, maximum, and minimum values of the estimated heart rate for each ROI strategy, as well as the mean absolute error (*MAE*) and Spearman's rank correlation coefficient.(10,16) Among these metrics, *MAE* was used to quantify the average absolute difference between the EVM-derived heart rate estimates and the ECG reference values, as shown in Eq. (1).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

Here, n denotes the number of valid samples, $\hat{y}_i$ denotes the EVM-based heart rate estimate for the i-th participant, and y_i denotes the ECG-derived actual heart rate for the i-th participant. A lower *MAE* indicates a smaller overall discrepancy between the noncontact estimation results and the ECG reference values.

In addition, Spearman's rank correlation coefficient was used to evaluate the consistency of the inter-participant ranking trends between the EVM-based heart rate estimates and the ECG reference values. Spearman's correlation is suitable for cases involving a small sample size, data that may not satisfy the normality assumption, or analysis of the monotonic relationship between two variables. It is defined as shown in Eq. (2).

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{2}$$

Here, ρ_s denotes Spearman's rank correlation coefficient, d_i represents the difference between the ranks of the two variables for the i-th participant, and is the sample size. As ρ_s approaches 1, the ranking trend between the EVM-based estimates and the ECG reference values becomes more consistent. Conversely, as ρ_s approaches 0, the monotonic association between the two measurements becomes weaker.

2.5 Feasibility criteria and evaluation benchmarks

Because this study is framed as a feasibility analysis, we predefined the level of agreement that would constitute feasibility for the intended application on the basis of two primary considerations. First, the proposed method is designed to function as an auxiliary, minimally intrusive tool for tracking physiological responses in older adults with dementia during assessments; it is explicitly not intended to replace ECG for clinical diagnosis. Second, feasibility was treated as a staged construct: the present study addresses Stage 1 (baseline feasibility under a controlled environment), whereas robustness under real-world horticultural activity was defined as an independent Stage 2 criterion to be validated in future work.

As an external reference, a research-grade eight-channel biosignalsplux data-acquisition system paired with OpenSignals software and a dedicated ECG sensor was used for physiological data collection. On the software side, the algorithms in the OpenSignals (r)evolution heart rate variability (HRV) analysis add-on compute the heart rate (HR) and time- and frequency-domain parameters in accordance with the measurement and physiological interpretation guidelines jointly established by the European Society of Cardiology (ESC) and the North American Society of Pacing and Electrophysiology (NASPE). However, it must be explicitly stated that this equipment is research-grade and has not received regulatory clearance as a clinical diagnostic device. Within the heart rate range observed in this cohort (~70 beats/min), a clinical diagnostic-grade device typically exhibits a standard tolerance of approximately ±5% to ±10%. This level of diagnostic accuracy was regarded as a long-term objective and an out-of-scope ceiling, rather than a direct acceptance criterion for the present auxiliary-monitoring feasibility study. Accordingly, the following evaluation criteria were adopted for Stage 1 feasibility.

- (C1) Accuracy: The group-level mean bias of the preferred ROI strategy should approach zero (with an absolute bias within a few beats/min), and *MAE* must fall within the ≤10 beats/min tolerance band commonly used as an acceptance threshold in PPG evaluation.
- (C2) Trend consistency: Because the core function of an auxiliary tool is to track inter-individual or relative heart rate trends rather than absolute diagnostic values, the estimates should exhibit at least a moderate positive monotonic association with the ECG reference (Spearman's $\rho \geq 0.4$).
- (C3) Robustness and consistency: Comparisons among different ROI strategies should yield stable, physiologically interpretable differences, and the preferred strategy must demonstrate a smaller systematic bias.

A method satisfying criteria C1–C3 was considered to demonstrate preliminary (Stage 1) feasibility as an auxiliary monitoring approach, but to fail to meet diagnostic-grade accuracy explicitly.

The Stage 2 criterion—maintaining comparable accuracy and trend consistency under dynamic horticultural activities involving hand manipulation, tool use, postural changes, and variations in ambient illumination—was set as the target for subsequent field validation and remains beyond the scope of this controlled-environment study.

2.6 Statistical analysis

Descriptive statistics were first used to summarize the heart rate estimation results obtained under different ROI selection strategies, including the mean, standard deviation, maximum value, minimum value, and *MAE*. These statistics were used to compare the estimation stability and error performance between the large-area ROI and small-area ROI strategies. Subsequently, to evaluate the association between the EVM-derived heart rate estimates and the ECG reference values, Spearman's rank correlation coefficient was used to examine the monotonic relationship between the two measurements. This analysis was further used to determine whether different ROI selection strategies could reflect heart rate variation trends consistent with ECG measurements.

Considering the limited sample size of this study and the fact that the participants represented a preliminary feasibility cohort of older adults with dementia, the data distribution may not necessarily satisfy the assumption of normality. Therefore, nonparametric statistical methods were adopted for correlation analysis to improve the robustness and applicability of the analytical results. This statistical strategy is more appropriate for small-sample studies, clinically specific populations, and exploratory engineering validation research. Overall, the purpose of the statistical analysis in this study was not to establish a generalizable clinical diagnostic model, but rather to preliminarily validate the feasibility, stability, and future application potential of EVM combined with dorsal hand imaging for NHRM in older adults with dementia.

3. Results

3.1 Participant characteristics and valid sample overview

A total of 16 older adults with dementia were recruited in this study. Among them, the dorsal hand image data and ECG reference data of 14 participants met the criteria for subsequent analysis and were therefore included in the feasibility analysis of noncontact heart rate estimation using EVM. Because the objective of this study was to preliminarily evaluate the feasibility of applying EVM combined with dorsal hand imaging to heart rate estimation in older adults with dementia, the valid samples were primarily used to compare the effects of different ROI selection strategies on estimation error and correlation trends, rather than to establish a predictive model for clinical diagnostic use.

3.2 Descriptive statistics of different ROI selection strategies

The heart rate estimation results of the 14 valid participants under different ROI selection strategies are summarized in Table 1. The mean estimated heart rate was 71.00 ± 5.66 beats/min for the large-area ROI strategy and 74.64 ± 5.99 beats/min for the small-area ROI strategy,

Table 1
Descriptive statistical results of different ROI selection strategies.

Statistic	Large-area ROI selection	Small-area ROI selection	ECG-derived heart rate
Mean ± standard deviation (beats/min)	71.00 ± 5.66	74.64 ± 5.99	70.14 ± 11.31
Maximum value (beats/min)	81	84	100
Minimum value (beats/min)	61	61	50
Mean absolute error, *MAE* (beats/min)	9.00	9.93	—
Spearman's	0.516	0.434	—
Value	0.059	0.118	—

whereas the mean ECG-derived heart rate was 70.14 ± 11.31 beats/min. In terms of proximity to the reference mean, the large-area ROI estimates were closer to the ECG reference values, suggesting that information extracted from a broader dorsal hand region may better reflect the overall trend of heart rate variation.

Regarding the estimation range, the maximum and minimum values obtained using the large-area ROI strategy were 81 and 61 beats/min, respectively. For the small-area ROI strategy, the corresponding maximum and minimum values were 84 and 61 beats/min, respectively. In contrast, the ECG-derived heart rate ranged from 50 to 100 beats/min. These results indicate that although image-based heart rate estimation can reflect certain interindividual differences, its estimated range was narrower than that of the ECG reference values. This finding suggests that the current EVM-based dorsal hand imaging method remains limited in sensitivity to the full range of physiological variability. In other words, the EVM-derived estimates may be more capable of reflecting group-level average trends, whereas their ability to identify cases with extremely low or high heart rates still requires further improvement.

3.3 Error and correlation comparisons

For the error analysis, the *MAE* of the large-area ROI selection strategy was 9.00 beats/min, whereas that of the small-area ROI selection strategy was 9.93 beats/min. This result indicates that the overall estimation error of the large-area ROI was slightly lower than that of the small-area ROI, suggesting that dorsal hand image information acquired over a broader spatial region may help reduce biases in heart rate estimation caused by local noise, specular reflection, or minor motion.

For the correlation analysis, the Spearman's rank correlation coefficient between the large-area ROI estimates and ECG-derived heart rate was $\rho = 0.516$ with $p = 0.059$. In contrast, Spearman's rank correlation coefficient between the small-area ROI estimates and ECG-derived heart rate was $\rho = 0.434$ with $p = 0.118$. Overall, the large-area ROI showed better consistency with ECG measurements in terms of heart rate ranking trends than the small-area ROI, and its correlation approached the conventional threshold for statistical significance. However, because $p = 0.059$ did not reach the commonly used significance threshold of $p < 0.05$, we should not directly claim that the correlation between the large-area ROI estimates and ECG-derived heart rate was statistically significant. Instead, the result should be interpreted more cautiously as indicating a moderate positive correlation trend that approached statistical significance. This finding supports the greater estimation potential of the large-area ROI, although further validation using a larger sample size and a more comprehensive experimental design remains necessary.

3.4 Summary of principal findings

Taken together, the results indicate that, for image-based heart rate estimation from dorsal hand images of older adults with dementia, the large-area ROI produced estimates closer to the mean ECG-derived heart rate, a lower *MAE*, and a higher Spearman's correlation coefficient than did the small-area ROI. This finding suggests that, under conditions in which age-related skin surface heterogeneity, differences in local vascular distribution, variations in optical reflection, and minor hand tremor may coexist, the spatial averaging effect provided by a larger ROI may help reduce the effect of abnormal signals from a single local region on the overall estimation results.

This result also indicates that dorsal hand image-based heart rate estimation should not rely solely on localized small-area signals, particularly in older adults with dementia. In this population, reduced hand stability, skin aging, and nonuniform local reflection may increase variability in signal quality. In comparison, the large-area ROI can integrate more spatial information and reduce the influence of point-wise noise on physiological rhythm extraction, thereby improving the robustness of noncontact heart rate estimation. Nevertheless, because the current estimation range was narrower than that of ECG and the statistical results did not reach significance, the present findings should be regarded as preliminary feasibility evidence rather than as conclusive validation of clinical accuracy.

When evaluated against the *a priori* feasibility criteria defined in Sect. 2.5, the large-area ROI strategy satisfied all three Stage 1 criteria. Its *MAE* of 9.00 beats/min fell within the $\leq$10 beats/min acceptance band (C1); its Spearman's ρ of 0.516 exceeded the 0.4 threshold for a moderate positive monotonic association (C2); and it exhibited a markedly smaller systematic bias than the small-area ROI (+0.86 vs +4.50 beats/min) (C3). Taken together, these results indicate that the large-area ROI strategy meets the predefined criteria for feasibility as an auxiliary, trend-level monitoring tool but does not achieve diagnostic-grade accuracy, and that the Stage 2 robustness criterion under real horticultural conditions remains unassessed in the present controlled-environment study.

4. Discussion

In this study, we employed an EVM-based noncontact physiological monitoring framework to estimate heart rate from dorsal hand images of older adults with dementia, using ECG as the reference standard. The estimation performance of different ROI selection strategies was compared. The results showed that the large-area ROI selection strategy outperformed the small-area ROI in terms of proximity to the ECG-derived mean heart rate, *MAE*, and Spearman's correlation trend. These findings preliminarily support the feasibility of applying EVM to heart rate estimation from dorsal hand images in older adults with dementia and further indicate that ROI selection may be an important factor affecting the stability of noncontact heart rate estimation.

The main contribution of this study lies in applying EVM to dorsal hand image analysis in older adults with dementia and preliminarily validating its potential as a minimally intrusive physiological monitoring tool. Previous NHRM studies have commonly used facial images as the primary analytical source. However, for older adults with dementia, facial imaging may involve concerns related to privacy, psychological stress, and cooperation. In comparison, dorsal hand imaging is less associated with facial identification and personal privacy concerns. Moreover, the hands are the principal body parts involved in horticultural activities. Therefore, establishing a stable method for extracting physiological signals from dorsal hand images may support the future development of a more natural, low-burden, and continuously trackable physiological assessment approach during horticultural therapy or geriatric care activities.

From the perspective of horticultural therapy assessment, our findings have methodological implications. Horticultural therapy emphasizes participant engagement, manual operation, sensory stimulation, and emotional regulation within naturalistic contexts. If the assessment process relies excessively on adhesive sensors or wired equipment, it may alter participants' activity patterns and psychological states, thereby reducing the naturalness and ecological validity of the intervention context. Accordingly, a noncontact measurement method that can be benchmarked against ECG and demonstrates preliminary feasibility may serve as an auxiliary physiological assessment tool during horticultural therapy in the future. However, it should be emphasized that the measurements in the present study were conducted under standardized dark-box and controlled illumination conditions, and the method has not yet been directly validated in real horticultural activity settings. Therefore, this study should be more appropriately characterized as an early-stage engineering validation for horticultural therapy assessment rather than as a completed real-world field validation.

From a technical perspective, EVM is highly sensitive to subtle image variations. This characteristic enables it to amplify minute color variations or subpixel displacements caused by microvascular blood-flow changes in the dorsal hand. However, the same sensitivity may also amplify nonphysiological signals. For example, minor hand tremor, involuntary movements, slight postural adjustments, and local tendon movement, which are commonly observed in older adults with dementia, may be amplified after EVM processing and become interference signals that affect the stability of heart rate estimation. If a small-area ROI is located in a region with greater tremor amplitude, weaker vascular signals, or stronger surface reflection, local noise may substantially affect the estimation results. In contrast, a large-area ROI can reduce the influence of isolated local abnormalities on overall signal estimation by covering more spatial information, thereby producing a more stable spatial integration effect.

In addition, the dorsal hand skin of older adults is not a homogeneous medium. Different locations may exhibit different optical reflection and pulsation characteristics because of variations in vascular distribution, skin thickness, wrinkles, tendon protrusion, pigmentation, and surface gloss. Therefore, applying EVM to older adult populations is not merely a problem of image magnification; rather, it involves the interactions among ROI selection, illumination control, skin surface heterogeneity, and motion artifacts. The superior performance of the large-area ROI observed in this study may not be attributable solely to its larger area. Instead, it may result from the integration of weak physiological signals from more spatial locations, allowing the overall estimation results to better represent dorsal hand pulsation characteristics. This observation further suggests that future improvements in dorsal hand image-based heart rate estimation should include the development of automated ROI selection, reflective-region exclusion, motion artifact suppression, and multiregion signal fusion algorithms.

The present findings can also be compared with those of related studies on EVM-based amplification of subtle motion.[18] Williams *et al.* reported that EVM can amplify extremely small tremors that are difficult to perceive with the naked eye, thereby making subtle hand tremor characteristics easier to observe and interpret.[18] This characteristic demonstrates the high sensitivity of EVM in extracting physiological and motion-related signals. In the context of the present study, EVM may enhance weak dorsal hand pulsation signals; however, it may also simultaneously amplify minor hand tremors or involuntary movements in older adults. Therefore, when applying EVM to NHRM in older adults with dementia, the key issue is not only to increase the magnification factor but also to distinguish cardiovascular pulsation-related signals from nonphysiological motion artifacts. Based on the present results, the large-area ROI may mitigate the influence of local artifacts on estimation performance because of its better spatial integration capability.

This study has several limitations. First, only 14 valid participants were included. The limited sample size resulted in insufficient statistical power; therefore, the present results should be regarded as a preliminary feasibility analysis rather than formal clinical validation. Second, the measurements were conducted in a controlled environment using a dark-box system and standardized illumination. Although this configuration helped reduce external interference and clarify the baseline performance of the EVM method, its estimation robustness has not yet been verified in real horticultural activity settings involving hand manipulation, tool use, postural changes, and ambient illumination variations. Third, although ECG was used as the reference standard, the current *MAE* remained approximately 9 beats/min. This level of error is not sufficient to support the use of EVM-based dorsal hand imaging as a replacement for ECG in clinical diagnosis. Therefore, a more appropriate positioning of this method is as an auxiliary, minimally intrusive physiological monitoring technique for horticultural therapy assessment rather than as a medical diagnostic-grade alternative measurement system.

Future research should be extended in three directions. First, the sample size should be increased, and participants with different levels of dementia severity, age groups, and skin conditions should be included to evaluate the generalizability of the method. Second, the measurement setting should be progressively advanced from the controlled dark-box environment to semi-natural and real horticultural activity settings to examine the signal quality and interference resistance of EVM under dynamic operating conditions. Third, more advanced image processing and signal analysis methods should be introduced, including automated ROI detection, motion compensation, reflection masking, frequency-band selection, multiregion weighted fusion, and heart rate quality indices, to improve estimation accuracy and robustness. If these issues can be addressed, EVM combined with dorsal hand imaging may become a promising low-contact physiological assessment tool for horticultural therapy, geriatric care, and nonpharmacological intervention research.

Overall, the most important value of the proposed NHRM strategy is that it provides an engineering pathway for extending horticultural therapy research. Specifically, it enables the acquisition of objective and continuously trackable physiological response information while minimizing interference with the natural activity state of older adults with dementia. Although the current results remain preliminary, they indicate that the combination of a large-area ROI and EVM provides better performance in dorsal hand image-based heart rate estimation and offers a concrete basis for subsequent real-world validation and algorithm optimization.

5. Conclusions

In this study, we investigated the feasibility of applying EVM to NHRM using dorsal hand images of older adults with dementia. ECG was used as the reference standard, and the estimation performances of large-area and small-area ROI selection strategies were compared. The results showed that, compared with the small-area ROI, the large-area ROI produced estimates that were closer to the ECG-derived mean heart rate, had a lower *MAE*, and exhibited a higher Spearman's correlation coefficient. These findings suggest that, under conditions involving age-related skin heterogeneity, differences in local vascular distribution, illumination variation, and minor hand tremor, a larger ROI may reduce the influence of local noise on heart rate estimation through spatial averaging, thereby improving estimation robustness.

Overall, EVM combined with dorsal hand imaging demonstrates preliminary application potential for noncontact heart rate estimation in older adults with dementia and may serve as a technical foundation for future low-contact and low-burden physiological monitoring tools in horticultural therapy assessment. However, this study remains a preliminary feasibility analysis and is limited by the small sample size, the use of a controlled dark-box measurement environment, and an estimation error that is not yet sufficient to support clinical diagnostic use. Therefore, before formal application in real horticultural activities or geriatric care settings, further studies to expand the sample size, strengthen algorithms for dynamic interference suppression, and validate signal quality, estimation stability, and practical feasibility under natural activity conditions are necessary.

Acknowledgments

This work was supported by the Agricultural Research Station's research project (No. 113a06). The authors thank the funding organizations for their financial support. The authors would also like to thank all the researchers cited in this article and the anonymous reviewers for their helpful comments and suggestions.

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