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Identifying patterns behind the changes in skin pores using 3-dimensional measurements and K-means clustering

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Abstract

Background: Skin pores are structural features of the skin, which tend to change as the skin ages. Since previous studies measured pores two-dimensionally, precise measurements using three-dimensional imaging were needed to comprehensively understand skin pores. This study aimed to determine the patterns behind the changes in skin pores during one's lifetime and to identify new characteristics of the pores in aged.

Materials and Methods: Skin surface profiles were measured three-dimensionally from the cheeks of 101 Korean women from February to March 2020 to analyze the exact state of their pores. The researchers performed K-means clustering to classify the skin pores, and topographical features of pores were analyzed as well. Statistical analyses were performed to verify the differences in the skin pore characteristics among clusters and the correlation between clusters and ages.

Results: Skin pores were classified into five groups based on size, density, and elongation. The skin conditions of the cluster groups were well correlated with aging, despite excluding age as a factor in pore classification. Adjacent skin pores tend to connect in the elderly.

Conclusion: Skin pores become larger and longer over time. Skin pores connect together in the elderly, which might be related to wrinkle formation. This phenomenon strongly suggests skin pores as a characteristic of aging skin and as a potential target for anti-aging treatment.

KEYWORDS

3D assessment of pores, aging, connecting phenomena of skin pores, K-means clustering, skin pores, skin surface, wrinkles

1 | INTRODUCTION

Skin pores are openings of the pilosebaceous follicles.[1] They are rarely visible at a younger age and tend to become larger and conspicuous as one gets older. Besides becoming larger, pores also become elongated as a consequence of aging.[2,3] Despite being natural structures of the skin, changes in pores throughout one's lifetime may imply that skin pores can be a characteristic of skin aging.

Many studies on skin pores have been conducted by two-dimensional (2D) imaging analysis. Controlled white light creates shades on the pores, allowing pictures to be taken. Then, the pores can be segmented using different colors between them and other skin surfaces. Such methods are easy and convenient to analyze the skin pores; however, given that the pores are structures located from the epidermis to the dermis, topographical information inside the "pores" is difficult to acquire by 2D imaging analysis.

Previous studies on skin pores revealed that certain pore characteristics are a consequence of aging; however, most of them relied on 2D imaging analysis, which might limit precise understanding of skin pores. To overcome this possible limitation, the researchers conducted a study on skin pores using three-dimensional (3D) analysis with the 3D in vivo optical skin imaging Primos®.[4] A previous study on skin pores reported that the findings from Primos® were highly correlated with changes in skin pores.[5] However, the measurements of the skin pores from that study were inaccurate due to the limitation of the built-in software of Primos®. The built-in software measures the cavity volumes in a given area without segmenting the pores exclusively. Therefore, it is hard to determine additional features of the skin pores other than their total volume. For detecting the precise shapes of skin pores, the researchers obtained the skin surface profiles and segmented each pore. Furthermore, as skin pore characteristics change with various factors, such as sizes, densities, and elongations, a comprehensive study that considered these factors was required to understand the patterns behind changes in skin pores.

For this comprehensive study of the changes in skin pores throughout an individual's lifetime, the researchers analyzed the skin pores of participants of varying ages. To investigate the patterns behind the changes in the skin pores, K-means clustering was used to classify the skin pores. K-means clustering allows the discovery of hidden structures of certain datasets.[6] Given that there are multiple features in the analyzed skin pores, classifying the pores based on several features would allow a comprehensive understanding of the changes in the skin pores. The cluster groups were further analyzed to determine whether aging affects the changes in the skin pores.

2 | MATERIALS AND METHODS

2.1 | Study participants

This cross-sectional study included 101 participants (age range: 3-68 years, average age: 36.6 years, standard deviation: 16.3). Korean women with healthy skin conditions were randomly recruited to participate in this study; women with skin diseases, such as atopic dermatitis, were excluded. The demographic information of the participants is presented in Table 1. To observe the changes in the pores in a wide age span, participants who were yet to attain puberty were also recruited. For participants aged <20 years, the measurement protocols were completely explained to their guardians, and they were accompanied by their guardians throughout the study process.

TABLE 1 Demographic information; numbers of the participants in each generation and their mean ages

	Measured side on face		
	Left	**Right**	**Total**
0-9	5	2	7
10-19	2	8	10
20-29	11	9	20
30-39	9	11	20
40-49	5	15	20
50-59	11	7	18
60-68	5	1	6
Total	48	53	101
Mean age (SD)	38.3 (18)	35.1 (14.7)	36.6 (16.3)

Abbreviation: SD, standard deviation.

The present study was carried out in accordance with the tenets of the Declaration of Helsinki and was approved by the Institutional Review Board of LG Household and Healthcare R&D Center. Written informed consent was obtained from each participant.

2.2 | Data acquisition

Measurements were taken from February to March 2020. Primos-CR® (Canfield Scientific) was used to obtain the participants' skin surface data. The left or right cheek was randomly chosen for each participant (Table 1). Participants were acclimated to a controlled atmosphere (temperature: 22± 2°C, relative humidity: 50 ± 10%) for 20 minutes before measurements.

2.3 | Data processing of skin pore variables

Segmentations and measurements of skin pores from the skin surfaces were performed by Newtone Technologies (France). First, the skin 3D surfaces were projected into the XY plane in order to create a 2D image called a depth map, where the intensity of each pixel corresponds to the Z-coordinate in the 3D-space. Then, the depth map intensities are normalized using a frequency high-pass filter. The resulting image has a dynamic centered on 0, with the skin cavities corresponding to negative intensities and the skin hills corresponding to positive intensities. From this depth map, both isotropic and anisotropic cavities are respectively segmented using specific shape enhancement algorithms. The two segmentations are added to obtain a single segmentation of all skin pores. Finally, pores outside the regions of interest (ROIs) were removed, and cavities <0.02 mm^2 were ruled out based on a previous study.[7] The processes of pore segmentation are illustrated in Figure 1.

For each distinct skin pore in the segmentation, size of the area and elongation were computed. The elongation was defined as the ratio of the major and minor axes. The values of Z-coordinate along

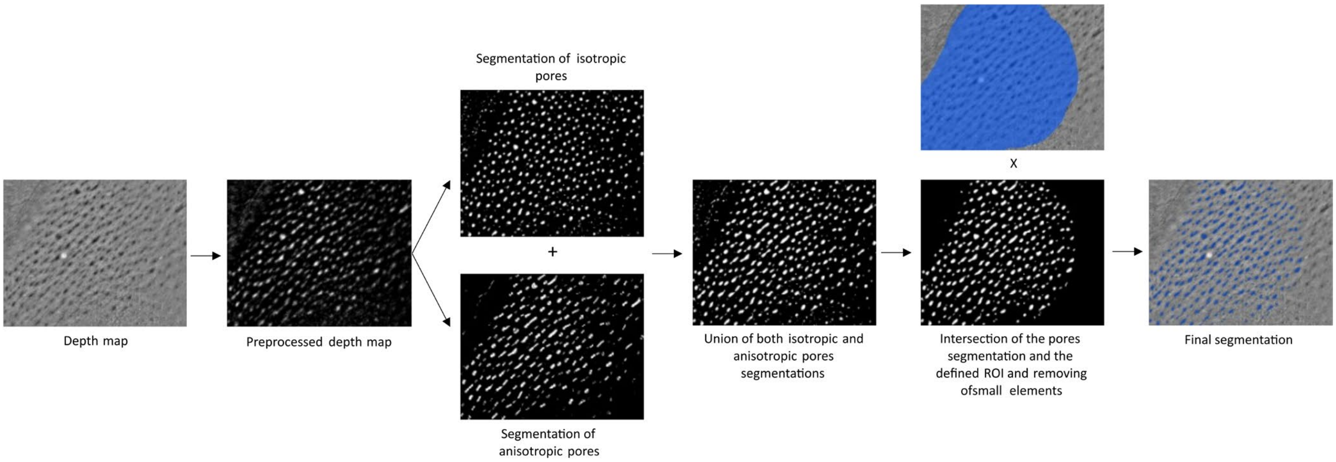

FIGURE 1 Processes of skin pore segmentation

the major axis were also computed to analyze topographical features of skin pores.

Data on the average area sizes (pore size), densities (pore density), and average elongations (pore elongation) of each participant were obtained as skin pore variables for further analysis. Pore density, calculated by dividing the total number of the skin pores by the area of ROI, represents detectable numbers of skin pores, not real density of pilosebaceous follicles, as their numbers do not change during a lifetime.

2.4 | Classifications of data using K-mean clustering

K-means clustering was performed using Python with Scikit-learn libraries.[8] The researchers performed clustering of the pore dataset using the following three features: pore size, pore density, and pore elongation. Using the Elbow method, the optimal number of clusters was decided for the dataset before clustering. The Elbow method determines the optimal K number using a plot of the sum of squared error (SSE) versus K numbers.[9] SSE is calculated as the error between each cluster centroid and data in the cluster; thus, SSE decreases as K increases. At some points, the slope of decrease begins to plateau, implying that the points are potential candidates for optimal K. After determining optimal K, K-means clustering was performed, and the mean ages of each cluster were calculated. The cluster groups were referred to as C_1, C_2, and so on in increasing order of mean ages of each cluster group. The protocols for the Elbow method and K-means clustering are described in the book by Hackeling and the study by Syakur et al[8,9] The mean values of pore variables and ages of each cluster were further compared to verify if the features were significantly different among clusters.

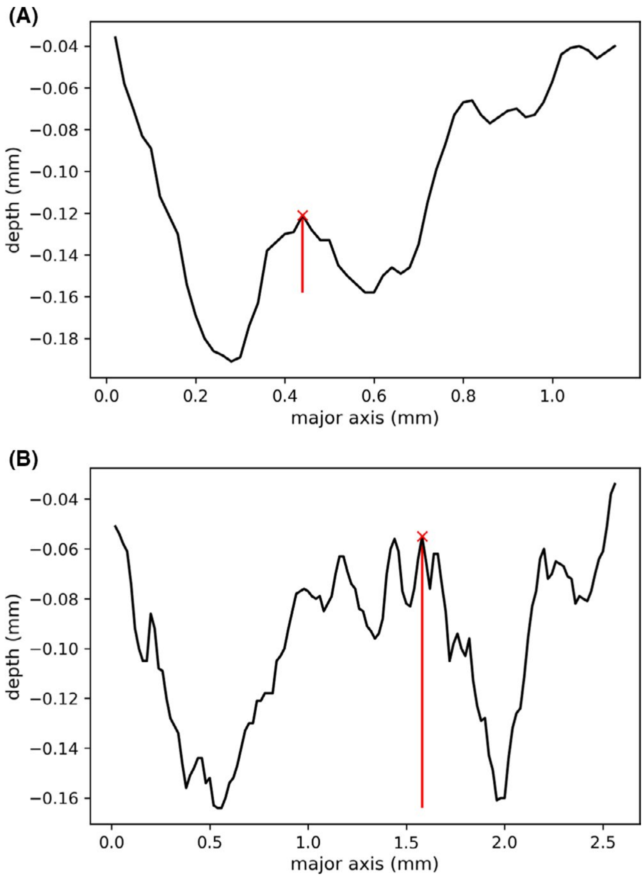

FIGURE 2 Processes of detecting connected skin pores. Red lines represent maximum height of prominent hills in each line profile. In A, the height of the hill is 19.4% comparing to total depth of the pore showing this line profile represents only one pore. Otherwise, the height of the hill is 81.5% comparing to total depth of the pore in B. The line profile of B can be assumed to have more than two pores in it

2.5 | Ratio of connected pores

Topographical features of segmented pores were examined as well to find out whether they were connected to each other. First, a line profile was plotted using the values of Z-coordinate along the major axis of each segmented cavity. Prominent hills along the line profile were selected, and heights were calculated. If the maximum height of the hills was higher than the criteria, the segmented cavity could be assumed to be actually more than two skin pores connected to each other. The criteria for the height of peaks were set to 0.7*[total depth of the line profile] (Figure 2). Analysis of topographical features was performed using Python with Scipy libraries. Number of connected pores was divided by number of total pores for each participant to obtain the ratio of connected pores, then mean values were compared among clusters.

2.6 | Statistical analysis

Spearman's correlation coefficient (r_s) between age and clusters was calculated to determine whether the changes in the skin pores represented by clustering were related to aging. Comparisons between clusters within pore variables, the mean ages, and the ratio of connected pores were performed using analysis of variance or the Kruskal-Wallis test, depending on whether the data in the groups were normally distributed and on the homogeneity of data between groups. The Shapiro–Wilk and Levene's tests were used to check the distribution and homogeneity, respectively. If significant differences were observed, the post hoc Tukey or Dwass-Steel-Critchlow-Fligner test was performed according to analysis of variance and the Kruskal-Wallis test respectively. The significance level was set to $P < .05$. Statistical analysis was performed using open-source software Jamovi v.1.19 [The Jamovi project (2020)].

3 | RESULTS

3.1 | Classifications of the skin pores

Using the Elbow method, 3 and 5 were selected as potential K numbers (Figure 3). To investigate the skin pores in the more segmented groups, the optimal number of clusters was decided to be 5. Pore size, pore density, and pore elongation of the 101 study participants are represented in a scatter plot labeled for each cluster (Figure 4). The five cluster groups were named C_1, C_2, C_3, C_4, and C_5. The numbers of participants in the C_1, C_2, C_3, C_4, and C_5 cluster groups were 11, 36, 16, 32, and 6, respectively (Table 2). The clusters and ages of participants were positively correlated ($r_s = 0.738$, $P < .001$).

3.2 | Comparisons of the skin pores and ages among clusters

Table 2 shows the mean values of the pore variables along with ages of each cluster. The pore size, the pore density, the pore elongation, and age were different among clusters ($P < .001$). The pore size increased from C_1 (0.0478 mm^2) to C_5 (0.277 mm^2) (Figure 5A). The pore density increased from C_1 (0.224 pores/mm^2) to C_3 (0.762 pores/mm^2) and decreased from C_3 (0.762 pores/mm^2) to

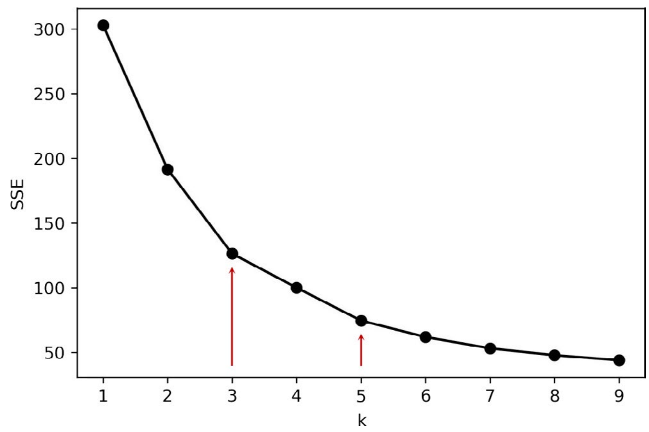

FIGURE 3 Results of the Elbow method for determining the optimal K number for K-means clustering. Bended points (3, 5) are potential K numbers

C_5 (0.497 pores/mm^2) (Figure 5B). The pore elongation increased slightly from C_1 (1.78) to C_3 (2.09), then increased rapidly from C_4 (2.37) to C_5 (3.92) (Figure 5C). Age increased from C_1 (10.1 years) to C_5 (55.8 years) (Figure 5D).

3.3 | Ratio of connected pores

Result for the ratio of connected pores is presented in Figure 6. C_1 and C_2 had no significant difference in the ratio of connected pores as well as C_3 and C_4. Other than these two pairs, significant differences were observed between each cluster.

4 | DISCUSSION

In this study, the researchers comprehensively analyzed the changes in skin pores as a consequence of skin aging. Skin pores can be classified into five clusters depending on their mean area, densities, and elongations. Clustering of skin pores was performed without the age variable, yet a positive correlation between clusters and ages of participants was observed. Therefore, patterns for changes in the skin pores are related to aging.

Changes in the skin pores throughout life are characterized as follows: first, the pores are small, and only a few pores can be detected (C_1) (Figure 5A, B). Then, the pores grow in sizes resulting increase in the number of detectable pores (C_2) and continue to increase to a high number of detectable pores (C_3) (Figure 5A, B). Pores continue to enlarge, but their detectable numbers begin to decrease, and they become elongated (C_4-C_5) (Figure 5A–C).

The skin pores of the C_1 group were distinctively smaller and had a lower density of detectable pores than those of other clusters (Figure 5A, B). The pore size and the pore density increased more than twice in the C_2 group, whereas no significant changes in the pore elongation were observed (Figure 5A–C). The mean

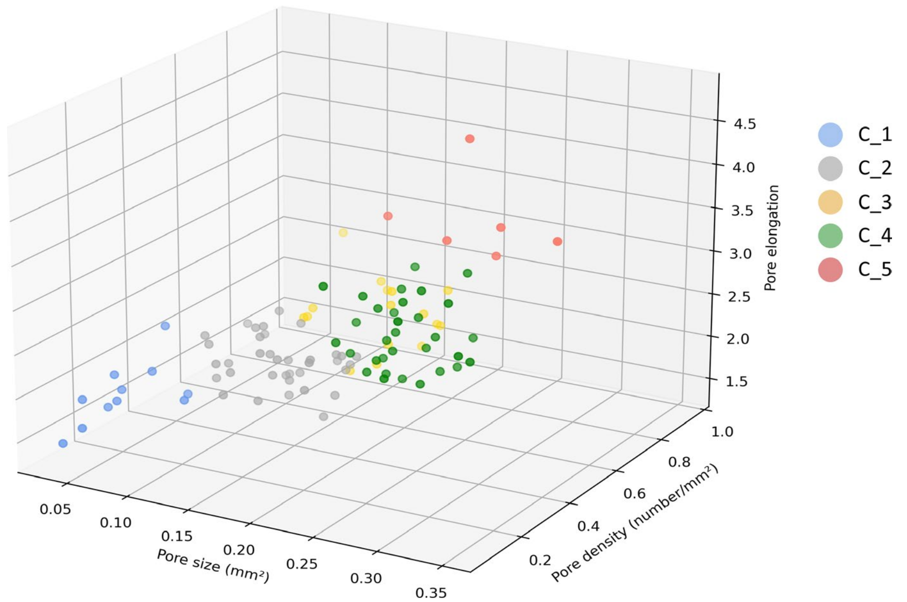

FIGURE 4 Scatter plot of the pore size, the pore density, and the pore elongation of the 101 participants

TABLE 2 Mean values of the pore variables and age of each cluster

	C_1	C_2	C_3	C_4	C_5	Total	P-value
N	11	36	16	32	6	101	
Pore size (mm^2)	0.0478	0.124	0.148	0.209	0.277	0.156	$P<0.001$[a]
Pore density (number/mm^2)	0.224	0.473	0.762	0.550	0.497	0.518	$P<0.001$[b]
Pore elongation	1.78	1.94	2.09	2.37	3.92	2.20	$P<0.001$[a]
Age	10.1	31.2	35.8	48.6	55.8	36.6	$P<0.001$[a]

[a]Comparisons between clusters were performed using the Kruskal-Wallis test.

[b]Comparisons between clusters were performed using analysis of variance.

ages of the C_1 and C_2 groups were 10.1 and 31.2 years, respectively, implying that the changes in the skin pores between the two clusters might occur due to pubertal development (Figure 5D). The increases in the insulin-like growth factor-1 (IGF-1) level, distinctive development of sebaceous glands, and increases in the amount of sebum secretion occur during the pubertal stage.[10,11] The IGF-1 level and amount of sebum secretion were reported to be correlated with sizes of skin pores.[12,13] The pore size of the C_2 and C_3 groups were not significantly different (Figure 5A), but their densities increase from C_2 to C_3 (Figure 5B). The mean ages of the two clusters were also not significantly different (Figure 5D), implying that other possible factors exist apart from aging, such as degrees of sebum secretion, skincare routine, and lifestyle, that are also responsible for the differences between the two clusters.

The pore density stops increasing and starts decreasing from C_3 (Figure 5B) while elongation begins to surge from C_4 to C_5 (Figure 5C). This tendency can be explained by the connecting phenomenon between adjacent pores. The ratio of connected skin pores showed that participants in C_5 have more connected pores than other clusters' participants (Figure 6).

Few studies have reported on the connecting phenomenon between adjacent skin pores. Bazin and Lévêque reported merging of pores and adjacent wrinkles,[14] and Jang et al showed connecting adjacent pores in some participants aged >50 years.[15] In this study, the researchers reinforce the connecting phenomenon of the skin pores with quantitative data (Figure 6). Referring to the line profiles of the connected pores (Figure 2), the skin surfaces between the pores seemed to be eroded. Thus, the line profiles appeared as "hills and valleys." Among the cavities with a "hill-and-valley" appearance, some looked like wrinkles.

The highlight of the present study includes applications of novel methods for measuring skin pores using 3D imaging analysis. With a high resolution of 20 µm to plane and 5 µm to depth, it was possible to measure skin pores precisely. Moreover, our study showed that K-means clustering can be utilized in the field of dermatology. It is hard to reveal the correlation between aging and skin features when the features do not show consistent changes; therefore, various features should be analyzed together. K-means clustering can be one option to solve this problem. Using these techniques, the patterns behind the changes in skin pores can be revealed, and the merging phenomenon of pores can be discovered. However, our study had

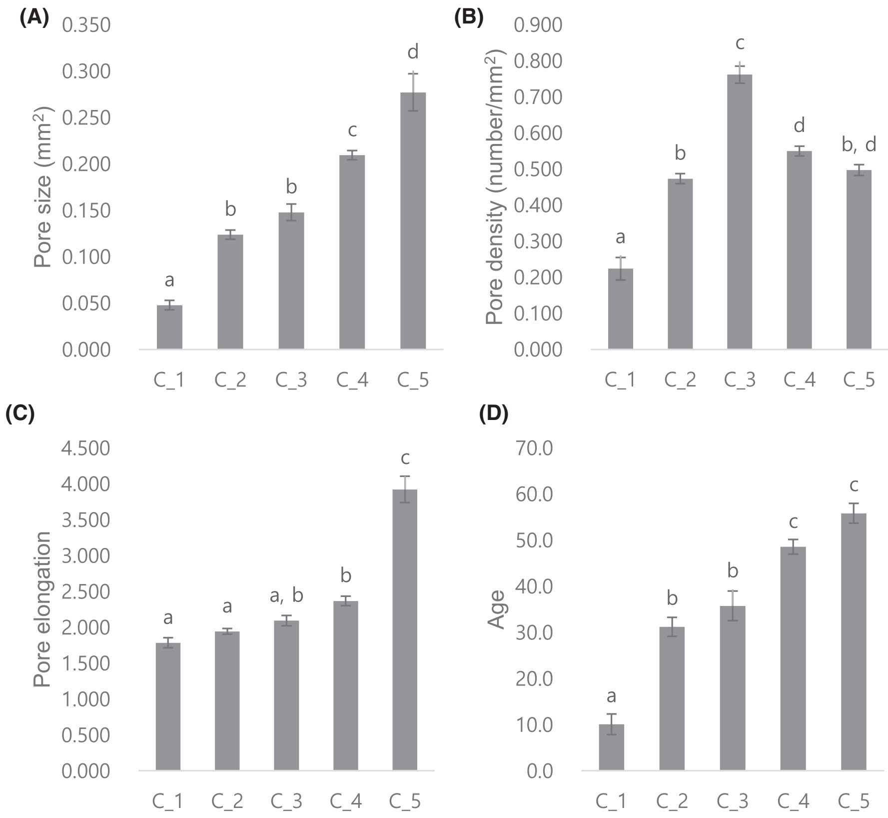

FIGURE 5 A, The pore size, the pore density, the pore elongation and the age of five clusters. Differences of alphabets on each bar graph represent the statistical differences tested by post hoc comparisons. Tukey test was used for the pore density (B), and Dwass-Steel-Critchlow-Fligner test was used for the other variables (A, C, D). Differences in the tendency can be observed among the four features

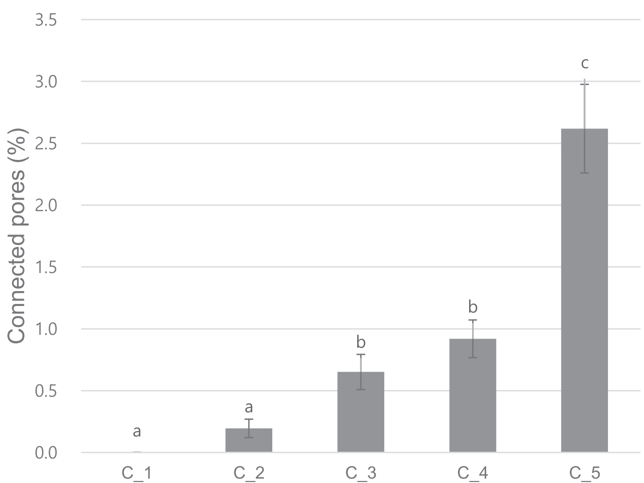

FIGURE 6 Ratio of connected pores in each cluster. Differences of alphabets on each bar graph represent the statistical differences tested by post hoc Dwass-Steel-Critchlow-Fligner test

some limitations. Data on variables regarding participant characteristics that might explain the changes in skin pores, such as skincare routine or lifestyle, were missing. Topographical anlaysis of skin pores for detecting connected pores should be improved as well, since the result of current study can only show occurrences of connected pores not numbers of connection in each segmented cavity. Some segmented cavities may include more than two pores in them, resulting significant increases in the pore elongation (Figure 5C) Our observations may imply that the skin pores play a role in the process of wrinkle formation; however, further studies should be conducted to determine whether the connecting phenomenon of the skin pores actually affects the formation of wrinkles.

5 | CONCLUSION

The skin pores can be classified into five groups according to the pore size, the pore density, and the pore elongation using a K-means clustering algorithm. The conditions of these five skin pore classifications are correlated with aging. Skin pores become larger and longer with age, with several pores eventually connecting to form long cavities that appear as wrinkles. This phenomenon strongly suggests skin pores as a characteristic of aging skin and as a potential target for anti-aging treatment.

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CONFLICTS OF INTEREST

None declared.

AUTHOR CONTRIBUTIONS

SL, MC, SG, and EJ performed the research. SL, EJ, JL, and SP designed the research study. SL, MC, and SG analyzed the data. SL, MC, SG, and EJ wrote the paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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