Abdominal-Deformation Measurement for a Shape-Flexible Mannequin Using the 3D Digital Image Correlation

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Abstract

In this paper, the abdominal-deformation measurement scheme is conducted on a shape-flexible mannequin using the DIC technique in a stereo-vision system. Firstly, during the integer-pixel displacement search, a novel fractal dimension based on an adaptive-ellipse subset area is developed to track an integer pixel between the reference and deformed images. Secondly, at the subpixel registration, a new mutual-learning adaptive particle swarm optimization (MLADPSO) algorithm is employed to locate the subpixel precisely. Dynamic adjustments of the particle flight velocities that are according to the deformation extent of each interest point are utilized for enhancing the accuracy of the subpixel registration. A test is performed on the abdominal-deformation measurement of the shape-flexible mannequin. The experiment results indicate that under the guarantee of its measurement accuracy without the cause of any loss, the time-consumption of the proposed scheme is significantly more efficient than that of the conventional method, particularly in the case of a large number of interest points.

Category: Computer Graphics / Image Processing

Keywords: Abdominal-deformation measurement; 3D digital-image correlation; Integer-pixel displacement search; Subpixel-registration resolution; Mutual-learning adaptive particle swarm optimization (MLADPSO)

I. INTRODUCTION

The morphology of the human body, especially the belly shape, is a crucial factor in areas such as apparel-customized services and body fitness. It is widely accepted that the accurate and effective attainment of the belly size and a building of a 3D belly profile are critical for the provision of a vital reference value for human fashion design. Generally, the existing studies concerning the measurement of the human-belly shape have been undertaken using a static scheme [1, 2]; however, the deformation measurement for different shapes should be taken into account in personalized fashion design. Unfortunately, a dearth exists regarding the studies that

consider this topic, so it is believed that the dynamic deformation measurement will become a salient future issue.

Digital image correlation (DIC) [3, 4] is a powerful and well-established noncontact optical metrology that is based on computer vision for full-field surface-deformation measurements. The DIC method that can be classified into 2D and 3D categories was first proposed by Peters and Ranson [5] in the 1980s. The 2D DIC with a single camera has been applied to a large variety of research fields [6], while the advanced 3D DIC [7] is utilized for 3D profile and deformation measurements due to its extreme practicality and effectiveness. Pan et al. [8] employed the pixel voxel to retrieve 3D deformed information. Pan and Wang [9] performed a DIC comparison of two subpixel-registration algorithms. The DIC method has been applied to the measurement of the dynamic foot-surface shape during the walking process [10]. Until the present time, the DIC technique has been improved significantly with the incorporation of gray interpolation methods [11], the shape function [12], the subset size [13], and various subpixel-registration algorithms [14].

DIC, however, is still limited by significant drawbacks that result in dissatisfactory effects in the practical applications. This problem is attributed to the following three issues. Firstly, it is assumed that an object deforms continuously and the gray-level intensity is constant, but when it confronts a large deformation, it is difficult to conform the supposition to the actual situation. The subsequent linear and nonlinear formulas are presented in the literature [15]. Nevertheless, this issue dramatically increases the cost that is owing to the additional parameters. Secondly, the common ideology deems that a set of adjacent points in a reference subset remains as the neighboring points in the target subset and the size of the rectangle subset is fixed. To address the DIC problems, the literature [16] discussed a number of improvement techniques including the first-order shape function and the second-order shape function. Undoubtedly, all of these improvements raise the complexity and the computational cost extremely. Finally, the feature points do not remain at the integer-pixel positions after a deformation. It is difficult to achieve the acceptable accuracy with a mere reliance on the integer-pixel search; consequently, the subpixel registration is indispensable. Substantial studies and experiments have proven that the Newton-Raphson (NR), Levenberg-Marquard (LM), and quasi-Newton (qN) methods are accurate and effective subpixel-registration algorithms. But the disadvantages of these algorithms that have been revealed in recent years, such as huge computational costs and local minimums with untrue values that make it difficult to satisfy the time-critical demands in real-time applications, need to be considered.

To avoid the previously mentioned drawbacks, the literature [17] developed an improved genetic algorithm (GA) for the subpixel registration of dual-energy computed tomography (CT) images. Most recently, particle swarm optimization (PSO) was successfully implemented to optimize the correlation coefficient function derived by by literature [18]. A novel optimization algorithm that is based on the improved GA and the PSO was used to optimize the parameters in a least squares support vector machine (LS-SVM) [19]. More important, the design of the algorithm still comprises strict requirements regarding the initial deformation guess. Zhang et al. [20] presented a hand-operated and computer-controlled interactive method. In this method, three or more distinct points on the undeformed image and their corresponding locations on the deformed image are identified manually. This approach is simple but not intelligent because of the low extent of automatization.

Lately, the fractal dimension of fractal geometry has been gradually developed as a quite active mathematic branch. The fractal analysis has been extensively used for the image analysis [21], feature extraction and matching [22, 23], pattern recognition [24], computer vision [25], and composite-material 3D reconstruction [26]. Its main characteristics are self-similarity and the calibration invariance.

In view of the previously mentioned deficiencies, the primary contributions of the paper can be summarized concisely as follows:

1. A novel feature vector consisting of a fractal dimension and a main subset direction is used for integer-pixel mapping based on the fractal-dimension theory.

2. Under the situation of an actual background, an elliptic subset is proposed according to an analysis of the deformation shape, while the subset size is simultaneously allowed to adjust adaptively in accordance with the deformation degree.

3. With a mutual-learning adaptive-PSO (MLADPSO) algorithm, integer-pixel positions that are obtained from a coarse search are regarded as the initial-guess estimations for the subpixel locations.

The goal of this paper is the exploitation of a novel methodology that enables an automatic measurement of the changed abdominal shape for different size groups.

The rest of this paper is organized as follows: The basic principle as well as the technology of the 3D DIC technique is presented in Section II; the details of the improved strategies are expounded in Section III; the results of numerical experiments and tests are discussed in Section IV; and lastly, the drawn conclusions are presented in Section V.

II. FUNDAMENTAL PRINCIPLE AND TECHNOLOGY FOR THE 3D DIC

A. Basic Principles of the Integer-Pixel Search

The existing DIC algorithm involves the following two

major steps: integral pixel (i.e., coarse search) and subpixel registration (i.e., fine search). In the integral-pixel search, the process comprises the tracking of the gray-value pattern in a small neighborhood called the *subset*. In general, a rectangle is centered at the interrogated point between the reference image and the deformed image. During the coarse search, the displacement field within the subset is assumed to be continuous and smooth. Besides, the movement of the displacement increment is constrained by an integer number of the spacing between the pixels. The tracking procedure is completed by a search for the peak position of the correlation-coefficient distribution. Once the maximum similarity is detected, the shape and the position of the target subset within the deformed image can be determined. The procedure is accomplished when all of the interest points have successfully obtained their own corresponding optimal points in the deformed image.

Nevertheless, it is necessary to mention that the feature points may become located between the pixels (i.e., subpixel location) while the deformation occurs. Thus, it is difficult to conform to the required precision in practical applications because of the derivation from the integer-pixel location. Undoubtedly, the fine-search resolution is considered as a critical technique for the improvement of the accuracy of the DIC method in the cases of certain hardware conditions.

B. Formalism of the Subpixel-Registration Resolution

The principle of the subpixel-registration resolution is shown in Fig. 1, where p is a center point in the reference subset at the coordinate (x_0, y_0), and the size is set as $(2M + 1) \times (2M + 1)$, called the *sample subset*; this sample subset corresponds to a subset in the deformed image called the *target subset* with another center point p' at the coordinate (x_0', y_0'), where q is a random point in the reference subset at the coordinate (x_i, y_j). The corresponding point in the target subset at the coordinate (x_i, y_i) is q', the displacement of which can be calculated using the following three mapping functions: *zero-order shape function*, *first-order shape function*, and *second-order shape function*.

The Newtonian algorithm, combined with a robust matching criterion and a high-accuracy subpixel registration, has been referred to as the gold standard for the subpixel registration. The Newtonian algorithm solves the nonlinear equations by directly employing the regularized cross-correlation coefficient as the optimization function. Pan and Li [27] put forward an improved NR method for the reduction of its complexity, enhancing its computational efficiency as well as strengthening its robustness. In spite of its achievement of the most accurate subpixel estimation, one significant shortcoming of the Newtonian algorithm is an extremely huge computational cost that is mainly
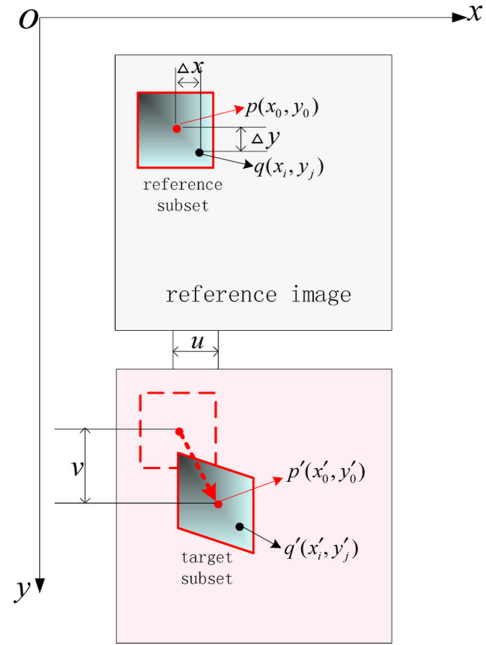
Fig. 1. Diagram of the digital image correlation (DIC) between the reference and deformed images.

due to its calculations of the first-order and second-order derivatives, especially regarding the 6×6 Hessian matrix.

C. 3D DIC based on Stereo Vision

Stereo vision [28] generally serves as a technique for the implementation of the 3D surface-profile reconstruction on the basis of two matched points from two different viewpoints. As shown in Fig. 2, the whole mapping process comprises the following two parts: stereo-matching in the horizontal part and the temporal matching between the original and deformed images from the same camera in the vertical part. p_l is a point in the left reference image at t_i, and its matching point in the right image is p_r. When the deformation occurs, p_l moves to a new position p_l' in the left reference image at t_{i+1}, and its matching point in the right deformed image also moves to p_r'. In this paper, the main focus is on the temporal-mapping procedure. Then, a series of improved alternative strategies are provided for the purpose of solving the substantial difficulties that often arise in deformation situations.

III. PROPOSED IMPROVED STRATEGIES

A. Novel Integer-Pixel Displacement-Search Method

1) Innovation of the Fractal Dimension based on the Subset Area

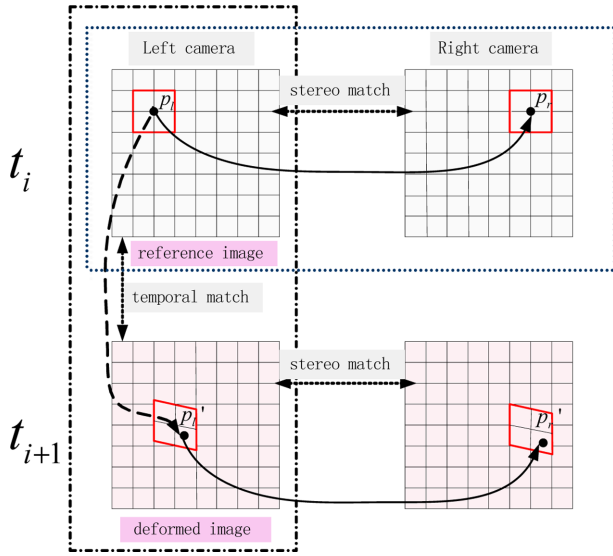The fractal dimension is an essential application in

Fig. 2. Diagram of 3D DIC matching process.

image processing. There are numerous ways to calculate the fractal dimension. In general terms, the box dimension is widely applied in image processing, where the entire area of an image is filled with boxes of the size δ (i.e., a cover). The variation of the size of δ causes the changes of the number of the boxes N_δ; that is, the smaller the size of δ, the higher the number of boxes.

The normal box-counting method of the fractal dimension for which the image is used is defined as follows:

$$D = \lim_{\delta > 0} \frac{\ln(N_r)}{\ln(1/r)}, \qquad (1)$$

where N_r denotes the requisite total box quantity for the coverage of the whole image, and r is the side of the box (i.e., the cover of r). A series of N_r can be obtained by a list of different r values, where $\ln(1/r)$ is taken as the x-axis, $\ln(N_r)$ is taken as the y-axis, and then the box dimension is a straight-line gradient that is obtained by means of the method of least squares.

The number of each cover is solely considered in Eq. (1), so the gray-level intensity and the probability for each cover are the substitutions of its numerator. Alternatively, by allowing for a variation of the side of the box according to the same proportion when the covered range is varied, the size ratio replaces the denominator in Eq. (1), and the new form is described as follows:

$$D_r = \lim_{\delta > 0} \frac{\sum f(i) \times p_i \times \ln(p_i)}{\ln(R/r)}, \qquad (2)$$

where R represents the image size.

The denominator in Eq. (2) can be also modified using the area ratio that is expressed, as follows:

$$D_s = \lim_{\delta > 0} \frac{\sum f(i) \times p_i \times \ln(p_i)}{\ln(S/s_r)} = \lim_{\delta > 0} \frac{\sum f(i) \times p_i \times \ln(p_i)}{\ln(R^2/r^2)} = \frac{1}{2}D_r. \qquad (3)$$

As can be seen, the fractal dimension of the area is half of the side value, and this ensures a shortening of the deviations between the different scales. This is demonstrated in Fig. 3, wherein the fractal-dimension calibration independence under the different-size conditions is implied.

2) Adaptive Adjustment of the Elliptic Subset

A rectangle subset is commonly employed in DIC. Actually, the shape of the correlated subset deforms in the large deformation that is shown in Fig. 4(a) and (b). Besides, with no deformation, the difference in the number of pixels that belong to the same-size subset is nonexistent. Whereas if the deformation of the object surface occurs, the quality of the pixels will change from the original to the deformed images, and this occurs even in subsets of the same size.

In this work, the tests of the abdominal-deformation measurement are conducted on a shape-flexible model with an installed gasbag. The representations of the existing studies show that the gasbag during its inflation can be regarded as a ball. Thus, the elliptic subset that is
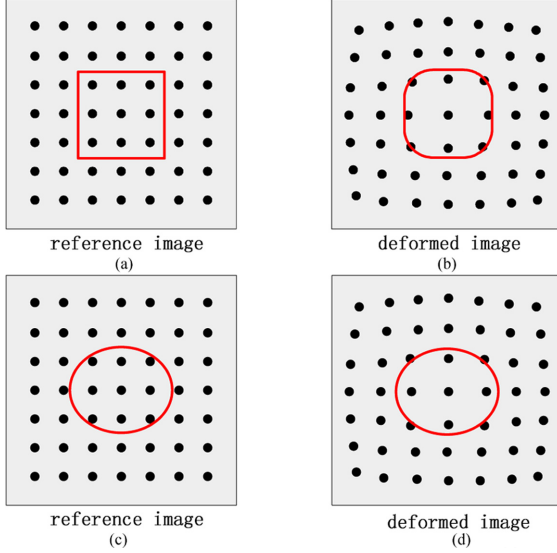

Fig. 3. Fractal dimensions of different forms.

Fig. 4. Subset of the deformation.

displayed in Fig. 4(c) and (d) is proposed. The subset-size accuracy is considered as a critical factor that is close to the accuracy of the measured displacement. A too-small subset size tends to result in a deterioration of the accuracy, while a too-large subset may cause an excessive computational cost. So the suitable size is achieved with a balance of the influences of the random and systematic errors.

It is clearly preferable to search a parameter to define the image-deformation degree on the basis of a subset. By doing so, it is practicable to evaluate the effect of the image-structure information of each image subset on the deformation measurement. To serve this purpose, an intuitive parameter called *subset structure density* is proposed here, whereby the subset size can be judged dynamically using the structural density depending on the extent of the deformation, as shown in Fig. 4(d).

$$\Gamma = \frac{\frac{\sum \left| f_i - \overline{f_i} \right|^2}{A}}{(\frac{1}{A}(\sum \left| f_i - \overline{f_i} \right|))^2}, \quad (4)$$

where f_i signifies the gray-level intensity within the subset, $\overline{f_i}$ denotes the mean of the gray-level intensity, and A is the gray number within the subset.

To ensure the reliability of the matching in the design of the adaptive subset, three steps are included. In the first place the major axis of the original elliptic size is set as 8 pixel and the minor axis is set as 6 pixel; in the second place, the associated Γ within the subset is determined and simultaneously set as the threshold; and finally, the new subset is acquired by an enlargement or reduction using the Step-2 pixels on the basis of the original size.

Moreover, without a direction factor, which may cause an error because of the insufficiency of the information

that is derived from the fractal dimension, the direction property that is required for the feature descriptor should be involved within the elliptic subset. The main direction is determined by the distribution of the peak gradient directions within the adjacent pixels around the key point. Therefore, the above proposed feature descriptor can be modified as a feature vector by

$$feature = [\, fractal \text{ dimension, main direction}].$$

Next, the adoption of the distance between the two feature vectors as the criterion of the similarity measurement of each interest corner proceeds as follows:

$$S_{ij} = \exp[-\left| F_l(i) - F_r(i) \right|],$$

where $\left| F_l(i) - F_r(i) \right|$ is termed as a distance measurement that is determined by

$$\left| F_l(i) - F_r(i) \right| = \left| fd_l(i) - fd_r(i) \right| \cdot \left| md_l(i) - md_r(i) \right|,$$

where *fd* denotes the fractal dimension and *md* is the main direction.

In specific applications, a suitable threshold for the similarity needs to be set in accordance with the accuracy requirement. If the similarity is greater than the threshold value, then the matching pair can be accepted and retained. The smaller the threshold value, the fewer the number of correct matchings, while a higher precision results in a more stable system.

B. MLADPSO Algorithm for the Subpixel Registration

The PSO is a stochastic algorithm. Literature [29] presented an improved PSO method for the parameter optimization of the image-distortion correction and mosaicking in a panoramic parking-assistant system for the automotive aftermarket. In literature [30], an adaptive PSO is introduced to estimate the real transformation angle for the sample point. In this paper, a novel MLADPSO algorithm that is utilized for the subpixel registration is introduced. The MLADPSO is an improvement based on the standard PSO that involves both an information mutual-learning mechanism and a dynamic adaptive-adjustment ideology in terms of the PSO. The operation of an adaptive regulation of the particle velocities ensures adaptability and diversity, and this plays a role in the avoidance of the trapping within the local extremum and results in fewer iterations. Besides, the previous optimal information is fully used in the initialization of the particle positions regarding the next feature point, which effectively improves the speed of the convergence.

In the uniform PSO, the learning factors r_1 and r_2, which are adopted to weigh the searching ability, were generally set at 2 empirically. For the sake of the closed
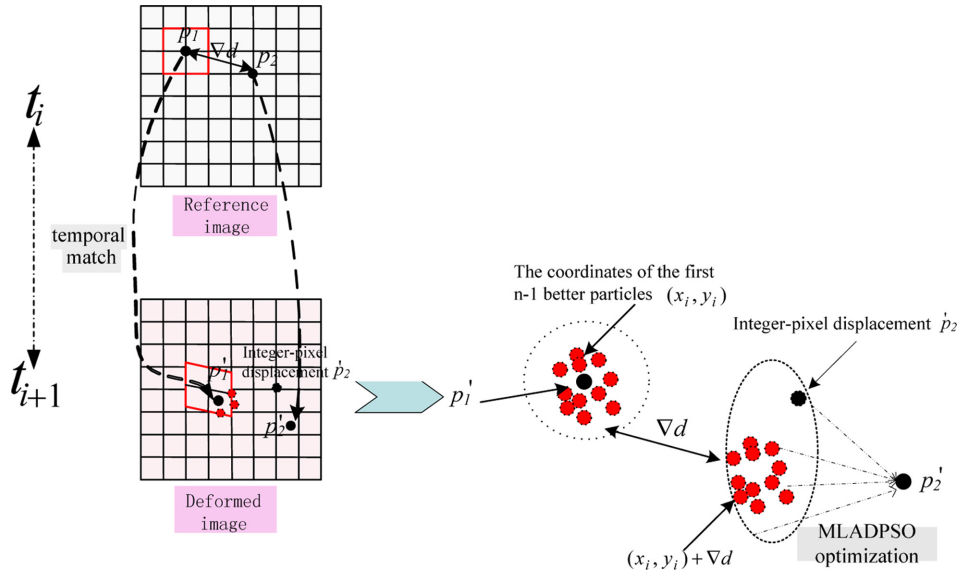
Fig. 5. The mutual-learning dynamic adaptive-particle swarm optimization (MLADPSO) diagram.

relation between the flight velocity and the range, it is indispensable to adaptively adjust the flight velocity. In this paper, an asynchronous strategy is implemented to adjust the learning factors to enhance the optimization. Considering the deformation differences of x and y in relation to the deformed-belly image, r_1 and r_2 were further refined into r_{1x} and r_{1y} and r_{2x} and r_{2y}, respectively.

It is assumed that the structural density of each feature point in the reference image is denoted by $\Gamma_{reference} = \{\Gamma_{r1}, \Gamma_{r2}, \Gamma_{r3}......\Gamma_{rn}\}$, while in the deformed image, it is denoted by $\Gamma_{deformed} = \{\Gamma_{d1}, \Gamma_{d2}, \Gamma_{d3}......\Gamma_{dn}\}$, and the variations between these two values can be expressed as $\Delta\Gamma = \{\Delta\Gamma_1, \Delta\Gamma_2, \Delta\Gamma_3......\Delta\Gamma_n\}$. r_1 and r_2 are assigned as follows:

$$r_1 = \begin{cases} r_{1m} & \Delta\Gamma_i = \max\Delta\Gamma \\ \dfrac{\Delta\Gamma_i}{\max\Delta\Gamma}\cdot r_{1m} & \Delta\Gamma_i = \min\Delta\Gamma, \\ \dfrac{\Delta\Gamma_i - \min\Delta\Gamma}{\max\Delta\Gamma - \min\Delta\Gamma}\cdot r_{1m} & \text{otherwise} \end{cases} \quad (5)$$

$$r_2 = \begin{cases} r_{2m} & \Delta\Gamma_i = \max\Delta\Gamma \\ \dfrac{\Delta\Gamma_i}{\max\Delta\Gamma}\cdot r_{2m} & \Delta\Gamma_i = \min\Delta\Gamma, \\ \dfrac{\Delta\Gamma_i - \min\Delta\Gamma}{\max\Delta\Gamma - \min\Delta\Gamma}\cdot r_{2m} & \text{otherwise} \end{cases} \quad (6)$$

where, generally, $r_{1m} = r_{2m} = 2$ when the pixel deformation degree reaches the largest vales of $r_1 = r_{1m} = 2$ and $r_2 = r_{2m} = 2$. The others are determined linearly according to the deformation degree.

The values r of the x-axis and the y-axis are respectively defined by

$$\begin{cases} r_{1x} = \dfrac{x_d - x_r}{x_d}r_1 \\ r_{2x} = \dfrac{x_d - x_r}{x_d}r_2 \end{cases} \quad (7)$$

$$\begin{cases} r_{1y} = \dfrac{y_d - y_r}{y_d}r_1 \\ r_{2y} = \dfrac{y_d - y_r}{y_d}r_2 \end{cases}, \quad (8)$$

where x_r and y_r are the coordinates in the reference image, x_d and y_d are the coordinates in the deformed image, and $\frac{x_d-x_r}{x_d}$ and $\frac{y_d-y_r}{y_d}$ indicate the deformed degradation on the x- and y-axes, respectively.

As shown in Fig. 5, with the aim of a search for the matched point with a higher precision in the right-view image that encounters the belly deformation for each detected corner in the reference image, the MLADPSO is implemented to obtain the subpixel coordinate values. In the MLADPSO, the parameters of each particle are referred to as the x- and y-coordinate values of each interest point. The number of particles is located at N. The initial values of the particle in the first iteration incorporate the integer-pixel value, namely $p_r(x_{coarse}, y_{coarse})$, derived from the integer-pixel displacement in the stereo matching, as well as the n-1 of the distance (Δd) values based on $p_r(x_{coarse}, y_{coarse})$. In the temporal matching, the Δd that is set randomly signifies the relative distance for the points such as p_l and p_l' in the reference and deformed images from the left view. The parametric n-1 can be denoted as ($p_r + \Delta d_1, p_r + \Delta d_2, ..., p_r + \Delta d_{n-1}$), and then the global best value (x_{gbest}, y_{gbest}) can be gained after multiple iterations. Next, with regard to the rest of the
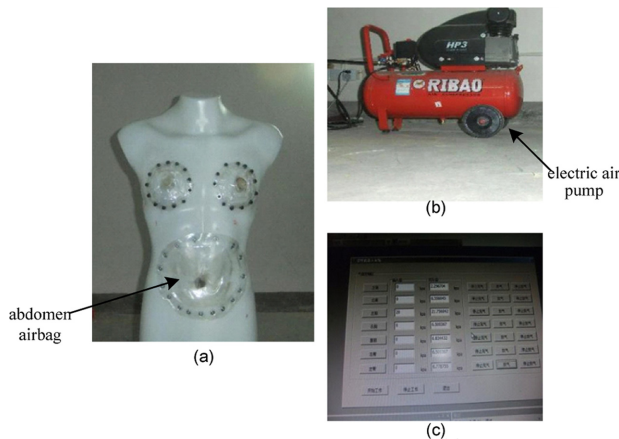
corners in the reference image, the initialization of the particles is defined in accordance with the mutual-learning property. The particle parameters are denoted as $((x_{gbest(1)}^{i-1}, y_{gbest(1)}^{i-1}) + \Delta d_1^{'}, (x_{gbest(2)}^{i-1}, y_{gbest(2)}^{i-1}) + \Delta d_2^{'}, ..., (x_{gbest(n-1)}^{i-1}, y_{gbest(n-1)}^{i-1}) + \Delta d_{n-1}^{'})$, and in the integer-pixel displacement stage, its own integer-pixel coordinate value is $p_r^i(x_{coarse}^i, y_{coarse}^i)$. $((x_{gbest(1)}^{i-1}, y_{gbest(1)}^{i-1}), (x_{gbest(2)}^{i-1}, y_{gbest(2)}^{i-1}), ..., (x_{gbest(n-1)}^{i-1}, y_{gbest(n-1)}^{i-1}))$ are the top best n-1 values from the former corner, and in the temporal matching, $\Delta d^{'}$ signifies the relative distances of $p_{l(i-1)}^{'}$ and $p_{l(i)}^{'}$ in the deformed image from the left view. The entire process continues until the subpixel registrations of all of the feature points are fulfilled.

IV. EXPERIMENTS AND ANALYSIS

A. Experimental Setup

In this section, the conduction of the experiments on the belly-deformation measurements of the shape-flexible model using the proposed methods is reported. The specific setup that is shown in Fig. 6 consists of the following two main parts: (I) A shape-flexible model with an installed airbag, as can be seen in Fig. 6(a); an electric air pump that is shown in Fig. 6(b); and the software platform of Fig. 6(c). The electric air pump uses the inflation of the airbag to vary the shape on the abdomen with different pressures. (II) A stereo-vision system composed of four Cyber-shot DSC-W3 CMOS cameras (Sony, Japan) with a resolution of 2816×2112 and an effective pixel quantity of approximately 6003000 pixel, as shown in Fig. 7, was utilized. The focal length of 18.9 mm (when it is converted to the 135-mm camera, the value is 114 mm) is arranged around the model, and the image size is 624×363 pixel. Two of the cameras (NO. 1 and NO. 2) were located as a pair at the front of the abdomen at an angle of 60°, and the other two cameras (NO. 3 and NO. 4) were arranged at the rear of the abdomen at the same angle. The frontal cameras were used to obtain the abdominal images, and the rear ones captured the images from the back part of the abdomen.

The abdominal images from the different perspectives are shown in Fig. 8. For a straightforward extraction of the feature points, a portion of the seams of a tight dress that was fitted onto the abdominal part of the shape-flexible model served as easily recognizable markers. The markers were designed as small bumps that are like approximate spheres. Here, 620 markers with a diameter of less than 2 mm are located separately on both the front and back pieces of the tight dress at the abdominal part.

The implementation of each test comprises the following four consecutive steps:

1. Separate extraction of the feature points in the reference and deformed images using the Harris method.

Fig. 7. Stereo-vision system.
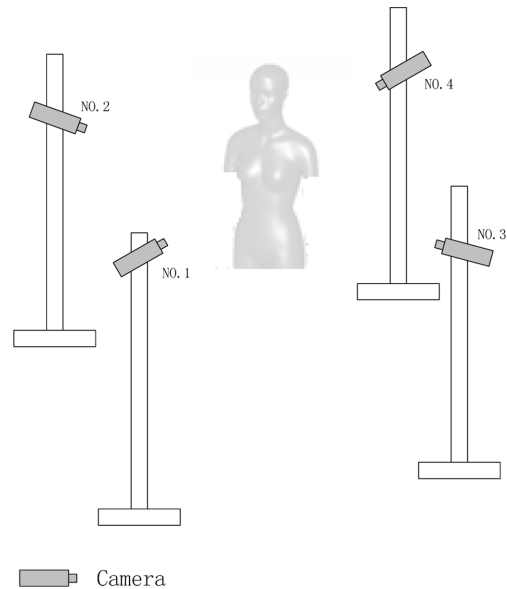
Fig. 6. Experimental setup. (a) A shape-flexible model with an installed airbag, (b) an electric air pump, and (c) the software platform.
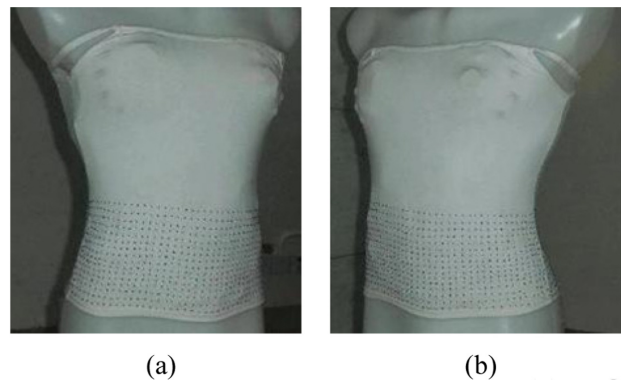
Fig. 8. Images from different views. (a) Frontal abdomen in left view (a) and right view (b).
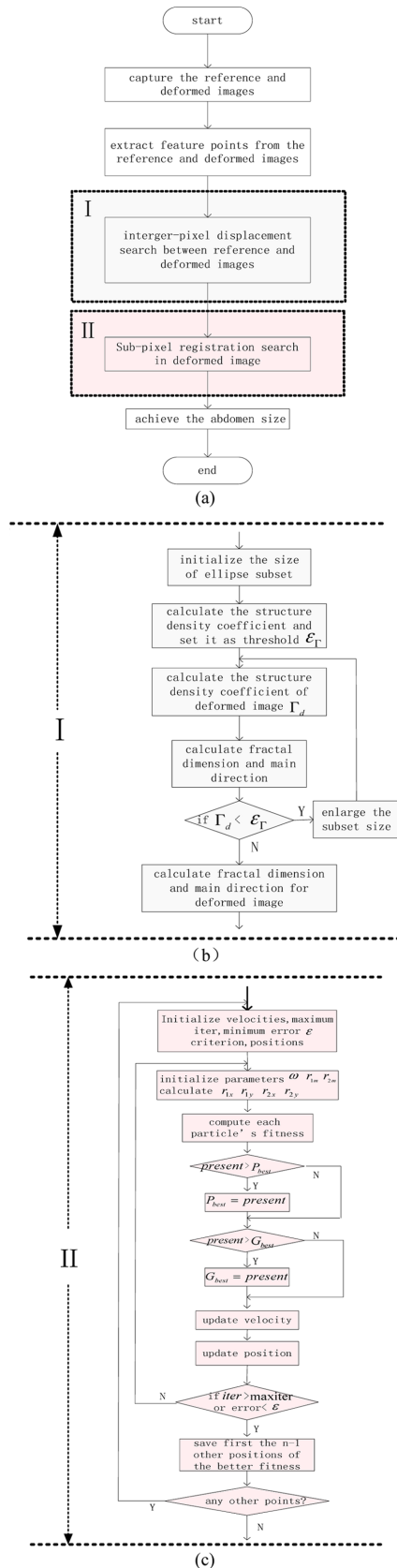
(a)　　　　　　　　(b)　　　　　　　　(c)
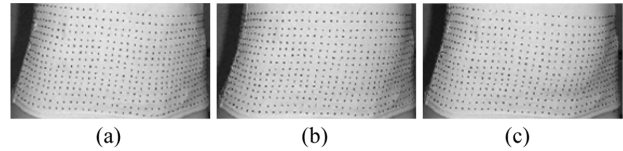
Fig. 10. Abdominal images from the left camera under different conditions. (a) Initial abdomen, (b) 10-kPa abdomen, and (c) 20-kPa abdomen.

2. Conduction of coarse tracking using the novel feature vector combined with the fractal dimension and the main direction to gain the integral-pixel positions.

3. Employment of the integral-pixel position as the initial-guess-value estimation for the subpixel fine search in the application of the MLADPSO.

4. Attainment of the various abdominal sizes that are associated with different barometric pressures by means of the recovery of a 3D abdominal model that is based on the stereo-vision system.

A flow chart is given in Fig. 9. The following subsections offer several tests regarding two typical cases in accordance with the different barometric-pressure choices. The concrete instructions are given as follows: the image shown in Fig. 10(a) shows the initial condition without any pressure in the abdominal airbag; Case 1, which is shown in Fig. 10(b), is the condition with the pressure of 10 kPa, and Case 2, which is shown in Fig. 10(c), shows the condition with the 20-kPa pressure. With the increase in the pressure, the deformation of the abdominal shape gradually occurred.

B. Integer-Pixel Displacement Search

In this subset, a coarse displacement search is performed in comparison with the conventional method that is based on the gray-level intensity within a fixed rectangle subset and the proposed method in the previously mentioned two cases. The coordinate errors in Tables 1–3 were calculated according to all of the mismatches from the initial matching in the integer-pixel displacement.

The contrast between the performance indicators with the specific parameters that are between the two approaches is listed in Table 1. *correct_match* is the correct matching rate that signifies the ratio of the number of absolute correct matching pairs without any errors to the total number of matched pairs. *recall_ratio* is the entire detectability that is determined by the ratio of the correct matched points to the total number of detected feature points. *T* denotes the mapping time-consumption. *Dev_x* and *Dev_y* are the errors of the integer pixel from the calculated value to the real value at the x-coordinate and the y-coordinate, respectively; here, *Mean_x* and *Std_x* denote the average error and the variance error of the x-coordinate, respectively, and the same meanings are applicable to the *Mean_y* and *Std_y* of the y-coordinate. As

Fig. 9. Flow chart. (a) Deformation matching, (b) integral-pixel deformation, and (c) subpixel registration.

Table 1. Analysis of coordinate errors between two cases in integer-pixel

	parameters		traditional method	proposed method
reference & case 1	correct_match (%)		70.11	95.36
	recall_ratio (%)		67.21	89.55
	T (s)		185.78	187.13
	Dev_X (pixel)	Mean_X	83.64	15.92
		Std_X	90.19	11.56
	Dev_Y (pixel)	Mean_Y	97.20	16.71
		Std_Y	70.07	12.41
reference & case 2	correct_match (%)		66.05	94.40
	recall_ratio (%)		64.50	88.12
	T (s)		288.91	302.32
	Dev_X (pixel)	Mean_X	145.8	24.97
		Std_X	111.99	16.61
	Dev_Y (pixel)	Mean_Y	121.64	27.72
		Std_Y	67.34	21.59

Table 2. Comparison of the distance error between two methods at Case 1 (pixels)

number	real value		traditional method		proposed method		distance_t	distance_p
	X	Y	X	Y	X	Y		
1	47	286	199	336	69	308	160.01	31.11
2	51	194	62	177	65	182	20.25	18.44
3	86	226	242	100	107	244	200.53	27.66
4	137	218	218	256	165	247	89.47	40.31
5	148	181	466	280	161	166	333.05	19.85
6	174	141	145	291	220	180	152.78	60.31
7	232	272	392	245	240	282	162.26	12.81
8	246	54	176	120	209	97	96.21	56.73
9	260	161	355	204	286	142	104.28	32.20
10	315	183	504	334	319	181	241.91	4.47
11	372	319	173	256	371	318	208.73	1.41
12	384	279	301	125	393	290	174.94	14.21
13	379	204	527	268	396	228	161.25	29.41
14	455	108	322	147	461	104	138.60	7.21
15	481	210	493	130	491	222	80.89	15.62
16	489	339	384	279	481	329	120.93	12.81
17	531	254	494	108	549	287	150.62	37.59
18	553	183	558	146	550	181	37.34	3.61
19	562	197	228	292	586	224	347.25	36.12
20	573	126	551	258	607	164	133.82	50.99
21	577	312	523	310	574	312	54.03	3.00
22	587	248	558	146	599	258	106.04	15.62
23	597	228	561	257	603	235	46.23	9.22
24	605	114	597	228	617	127	114.28	17.69
	minimal distance						20.25	1.41
	maximal distance						347.25	60.31
	mean distance						143.15	23.85
	standard deviation of distance						81.86	18.47

Table 3. Comparison of the distance error between two methods at Case 2 (pixels)

number	real value		traditional method		proposed method		distance_t	distance_p
	X	Y	X	Y	X	Y		
1	44	276	150	308	74	313	110.72	47.63
2	50	179	58	163	71	195	17.89	26.40
3	80	215	227	97	115	254	188.50	52.40
4	126	209	249	219	155	241	123.41	43.19
5	137	172	319	313	112	189	230.23	30.23
6	163	136	318	34	204	185	185.55	63.89
7	204	119	330	336	211	128	250.93	11.40
8	220	266	379	249	242	278	159.91	25.06
9	231	52	277	181	269	94	136.96	56.64
10	246	100	184	248	273	121	160.46	34.21
11	271	204	359	63	295	229	166.21	34.66
12	291	241	242	142	304	148	110.46	93.90
13	297	208	271	56	311	298	154.21	91.08
14	301	184	215	284	313	193	131.89	15.00
15	333	313	472	220	361	337	167.24	36.88
16	348	278	354	293	367	263	16.16	24.21
17	365	210	261	182	394	241	107.70	42.45
18	443	121	112	205	424	143	341.49	29.07
19	472	220	348	278	479	231	136.89	13.04
20	486	143	497	316	487	157	173.35	14.04
21	475	339	209	232	460	322	286.71	22.67
22	520	257	341	207	538	291	185.85	38.47
23	548	190	130	192	579	218	418.00	41.77
24	556	202	440	322	608	242	166.90	65.60
25	568	131	553	258	581	145	127.88	19.10
26	570	311	352	338	572	312	219.67	2.24
27	581	248	130	192	604	231	454.46	28.60
28	590	242	561	273	601	236	42.45	12.53
29	601	115	569	45	583	141	76.97	31.63
	minimal distance						16.16	2.24
	maximal distance						454.46	93.91
	mean distance						174.11	36.14
	standard deviation of distance						101.63	22.14

results that maintained a greater stability and a robustness with a mere slight decrease. Moreover, the deviations of the x and y locations of the proposed method are all dramatically smaller than those of the traditional approach despite the slightly longer time-consumption that was measured within an acceptable range. Overall, it is firmly believed that the proposed method is a valuable alternative tool for the coarse search that benefits from the extra-ordinary ability to achieve a high accuracy and a strong stability.

To confirm the efficiency, comparisons of 24 and 29 falsely matched pairs that were selected randomly between the two methods are given here, and the results are illustrated in Tables 2 and 3, respectively. *dis* tan *ce_t* and *dis* tan *ce_p* denote the distance errors from the utilizations of the traditional method and the proposed method, respectively. X and Y represent the coordinate values of the points. The statistical results given at the end of each table are the minimal distance, maximal distance, mean distance, and standard deviation of distance.

As can be easily confirmed from the tabulations, the results of the two methods in either case differ by several times; this is unlike the traditional method that produces large errors that are intensified with the increase in the

illustrated in Table 1, it is evident that the *correct_match* and the *recall_ratio* that were obtained using the proposed method are superior to those of the traditional method in both experiments, particularly under the large-deformation situation. That is, the previous two performance parameters were successfully implemented using the conventional solution that yielded sharp declines of different extents, whereas the proposed method produced
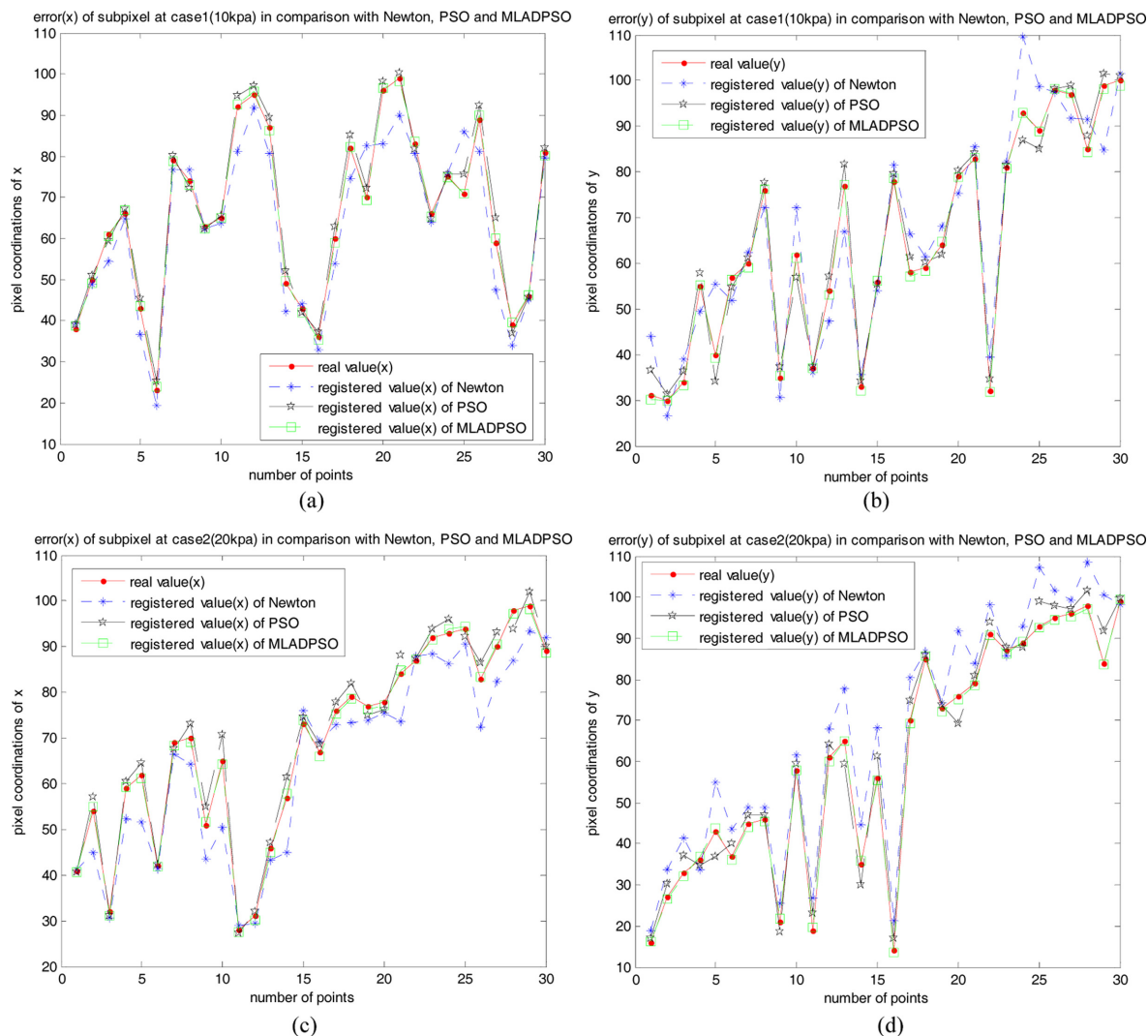
Fig. 11. Coordinate values of Case 1 and Case 2. (a, b) The x and y positions of Case 1. (c, d) The corresponding values of Case 2.

deformation. The results produced by the proposed method are basically slight deviations. This method is capable of maintaining a high stability because of the advantages of adaptability and recognition.

C. Subpixel-Registration Algorithm

It is worth noting that, as a nonlinear optimization algorithm, the Newtonian method requires an accurate initial guess to achieve a precise and rapid convergence. In the present paper, the integer-pixel coordinate values are taken as the initial-guess estimations in the subpixel iteration. In this subsection, the focus comprises comparisons of the Newtonian method, the uniform PSO, and the proposed method, MLADPSO.

A selection of 30 feature points that were taken from the total number were enacted randomly. The specific position values of the x-coordinate and the y-coordinate that are associated with each feature point are illustrated

in Fig. 11, where Fig. 11(a) and (b) reflect the x and y positions of Case 1, and Fig. 11(c) and (d) are the corresponding values of Case 2. The results demonstrate that the MLADPSO-achieved positions are much closer to the real values than those that were obtained by the Newtonian method and PSO. With the MLADPSO, the location accuracy is up to 10^{-6}, while only 10^{-4} was achieved with the use of the Newtonian algorithm. The PSO accuracy is between those of the other two methods.

In addition, in consideration of a full account of the performances of the two methods, the distance errors of the subpixel as well as the time-consumption is listed below in Tables 4 and 5, respectively. The tests were conducted on two cases where the points were increased from 50 to a maximum of 497. The *mean_dis* tan *ce* and *std_dis* tan *ce* denote the average error and the variance of distance, respectively, while *t* is the computational time that was expended in the subpixel registration. The statistical results revealed that the MLADPSO errors are

Table 4. Error analysis and time-cost comparison of subpixels at Case 1 (10 kpa)

NO	Parameters	Newton	PSO	MLADPSO
50	$mean\_dis\tan ce(pixel)$	8.42	3.44	0.96
	$std\_dis\tan ce(pixel)$	4.44	1.57	0.20
	t(s)	20.825	83.143	28.841
100	$mean\_dis\tan ce(pixel)$	8.59	3.69	0.96
	$std\_dis\tan ce(pixel)$	4.30	1.61	0.21
	t(s)	41.424	165.696	46.828
200	$mean\_dis\tan ce(pixel)$	8.44	3.50	0.96
	$std\_dis\tan ce(pixel)$	4.36	1.53	0.21
	t(s)	83.254	334.282	84.782
300	$mean\_dis\tan ce(pixel)$	8.28	3.49	0.96
	$std\_dis\tan ce(pixel)$	4.31	1.51	0.22
	t(s)	125.112	512.943	125.038
450	$mean\_dis\tan ce(pixel)$	7.84	3.38	0.95
	$std\_dis\tan ce(pixel)$	4.31	1.47	0.21
	t(s)	187.877	783.210	170.797
497	$mean\_dis\tan ce(pixel)$	7.93	3.37	0.96
	$std\_dis\tan ce(pixel)$	4.28	1.46	0.22
	t(s)	219.438	921.915	190.010

Table 5. Error analysis and time-cost comparison of subpixels at Case 2 (20 kpa)

NO	Parameters	Newton	PSO	MLADPSO
50	$mean\_dis\tan ce(pixel)$	10.25	3.89	0.99
	$std\_dis\tan ce(pixel)$	4.55	1.77	0.22
	t(s)	21.262	85.039	29.237
100	$mean\_dis\tan ce(pixel)$	10.25	3.86	0.99
	$std\_dis\tan ce(pixel)$	4.77	1.73	0.22
	t(s)	41.476	165.957	47.766
200	$mean\_dis\tan ce(pixel)$	9.14	3.79	0.98
	$std\_dis\tan ce(pixel)$	4.77	1.62	0.21
	t(s)	84.364	342.172	85.766
300	$mean\_dis\tan ce(pixel)$	8.92	3.93	0.98
	$std\_dis\tan ce(pixel)$	4.39	1.84	0.21
	t(s)	125.112	514.762	125.104
450	$mean\_dis\tan ce(pixel)$	8.32	3.85	0.97
	$std\_dis\tan ce(pixel)$	4.33	1.74	0.21
	t(s)	189.756	796.975	173.036
497	$mean\_dis\tan ce(pixel)$	8.21	3.89	0.97
	$std\_dis\tan ce(pixel)$	4.32	1.83	0.20
	t(s)	219.438	932.290	191.326

much smaller than those of the Newtonian method and PSO in both cases.

As can be seen in the tables, at the beginning, on the condition of a small quantity, the velocity of the Newtonian method is merely faster than that of the MLADPSO; but with the increasing of the quantity, the efficiency of the MLADPSO was gradually improved. Conversely, when the number was increased to 300, the MLADPSO is faster than the Newtonian method. Overall, the PSO speeds of the three algorithms are always the slowest. This advantage is primarily attributed to the mutual-learning mechanism that contributes to the minimization of the time-consumption of the initialization for each particle, while the repetitive random initialization operations that are required for the Newtonian method waste substantial time, leading to an efficiency decline. Meanwhile, the MLADPSO improves the accuracy but reduces the running time. In general terms, the utilization of the MLADPSO is strongly recommended for the subpixel registration, especially in the case where a particularly high accuracy and efficiency are obtained.

D. Analysis of the Shape Size

In order to evaluate the overall accuracy of the proposed method, it was tested on a shape-flexible model. The tests were completed using the respective pressures of 10, 20, and 25 kPa and three independent modellings and measurements, and the aim is the attainment of the belly circumference in the process. In the present work, the ultimate

Table 6. Error inspection of the abdominal size between measured and calculated values

Case (pressure)	Manual measured value (cm)	Proposed method value (cm)	Error (cm)	R_Error
10kpa	77.31	77.76	0.45	0.58%
20kpa	80.64	81.15	0.51	0.63%
25kpa	82.78	83.31	0.53	0.64%

abdominal size was obtained using a 3D-reconstruction technique that is based on the stereo-vision system after the completion of the coarse-fine search. The manual measurement is a traditional contact method. Comparisons of the parameters of the previous two schemes (manual measurement and the proposed method) were made. As shown in Table 6, the Error and the R_Error are the error and the relative error between the manual and proposed methods, respectively, in the three pressure-value cases. The results listed in Table 6 revealed that even with the existence of differences from the comparison with the measured values, the errors are merely minor and completely conform to the acceptable criteria in consideration of apparel design and engineering.

V. CONCLUSIONS

In this paper, an innovative 3D DIC formulation with a coarse-fine two-step method is proposed. Tests of the

abdominal 3D deformation measurements were carried out on a shape-flexible mannequin to validate the proposed method. The results of the integer-pixel examination revealed that the fractal dimension and the main direction are more feasible and reliable compared with those of the traditional method. The results derived from the subpixel-registration resolution demonstrated that the modified MLADPSO is more accurate with a higher computational efficiency, and this is in contrast to the Newtonian algorithm and PSO. In particular, the boosting of the iterative computations of the subpixels in the proposed method are gradual as the number of feature points are increased, and this occurs without any loss of the measurement precision.

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