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Selecting Promising Junior Swimmers in Egypt Using Automated Biometric Algorithms of Image Processing and Fuzzy Concepts

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ABSTRACT Modern sports need a great physical and psychological effort from young athletes to reach high performance levels. Stature length, leg length, foot length, arm length, hand length, shoulder width, hip width, chest width and weight are the anthropometric characteristics that affect swimmers' performances. This paper introduces new techniques to select promising junior swimmers in Egypt. It develops two automated algorithms to select junior swimmer depending on their anthropometric measurement. The first technique uses Canny filter to develop the first algorithm, while the second one uses the Fuzzy concepts. The proposed algorithms make use of the image processing technique to handle the anthropometric measurements, by detecting the human body feature points automatically from the front and side images. The 101 feature points extract automatically from 36 human body measurements, while swimming games needs only 8 body dimensions from these 36 human body measurements. Therefore, the proposed system is not limited to swimming sports but can also be applied to other sports. Moreover, the experimental results and the corresponding statistical analysis show the high accuracy and advantages of the proposed algorithms. The first algorithm improved the results that could have obtained using the well-known fully vision-based automatic human body method by 22.23%, 15.9%,29.41%, and 27.5%, for stature length, arm length, leg length, and shoulder width, respectively. Also, it gave the best results for Leg Length, and Shoulder width, while the second one yielded the best result for Stature Length.

INDEX TERMS Anthropometric measurements, feature extraction, image processing, swimming games, canny filter, fuzzy algorithms.

I. INTRODUCTION

Biometrics is the measurement and statistical analysis of physical and physiological characteristics. The main objective of biometrics is to create registration systems that can be used in the required application. Biometrics are used in sports to identify talent, injury risk, optimal performance characteristic for that individual, estimate readiness, movement analysis, and wearable devices [1]–[3]. On the other hand, a great conjunction arises in the last two decades between Artificial Intelligence (AI) algorithms and many aspects of sport sciences sectors. Fuzzy set theory and its principles was used for fuzzy clustering analysis in football team ranking [4], to build a fuzzy control model of the ping pong sport [5], to select the athlete candidate that meets the best performance criteria [6], to help coaches for selecting the best players to form a proper team, among a group of players, according to the desired match objectives [7], and evaluation of weight and strength training exercises, and hence enabling coaches the opportunity to enhance the athletes' performances [8]. Biometrics and AI are combined as an identification process to recognize elite players, by measuring physical, physiological, psychological and sociological attributes as well as technical abilities, either in isolation or in combination and hence it acts as a filter that chooses people who have a strong chance for success [9], [10]. The presented

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TABLE 1. The human body dimension.

No	Human body dimensions	Width	Depth	Height	Length
1	Head	✓	✓	-	-
2	Neck	✓	✓	✓	-
3	Shoulders	✓	✓	✓	-
4	Chest	✓	✓	✓	-
5	Abdomen	✓	-	✓	-
6	lower waist	✓	✓	✓	-
7	Hip	✓	✓	✓	-
8	Thigh	✓	✓	-	-
9	thigh (most inside point)	✓	-	-	-
10	Knee	✓	-	-	-
11	Shank	✓	✓	-	-
12	Ankle	✓	✓	-	-
13	Foot	✓	✓	-	-
14	Body	-	✓	-	-
15	pronasale to opisthocranion	-	✓	-	-
16	Stature	-	-	✓	-
17	Crotch	-	-	✓	-
18	Mouth to vertex	-	-	✓	-
19	Arm	-	-	-	✓
20	Hand	-	-	-	✓

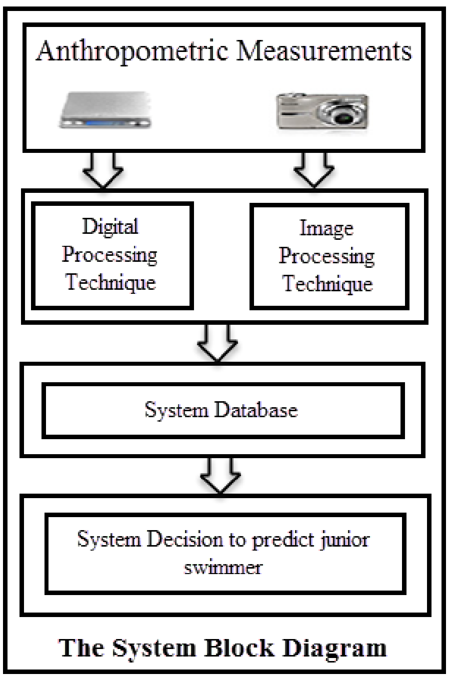


FIGURE 1. The block diagram of the proposed system.

paper aims to make use of this concept for junior swimming players.

Swimming sports have been studied from many perspectives, such as, anthropometric measurements using two-dimensional or three-dimensional measurements,

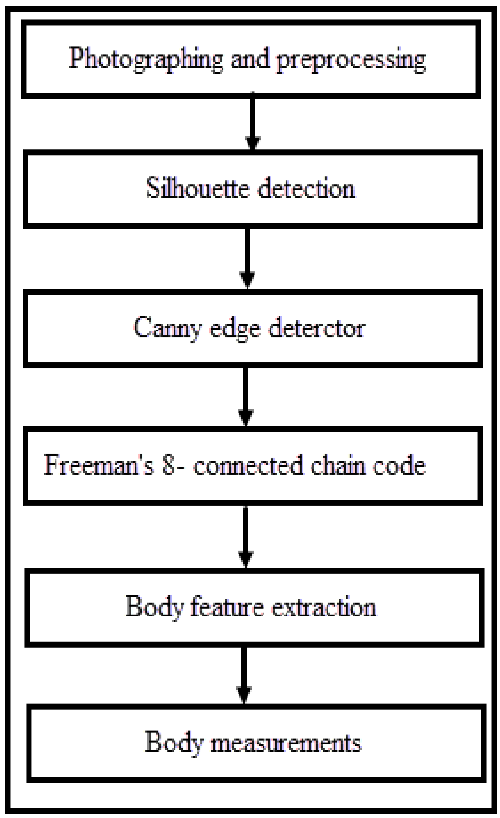


FIGURE 2. The algorithm of the image processing technique.

automatic or manual measurement, and swimmer's performances [26]–[34]. AI techniques have been used for many

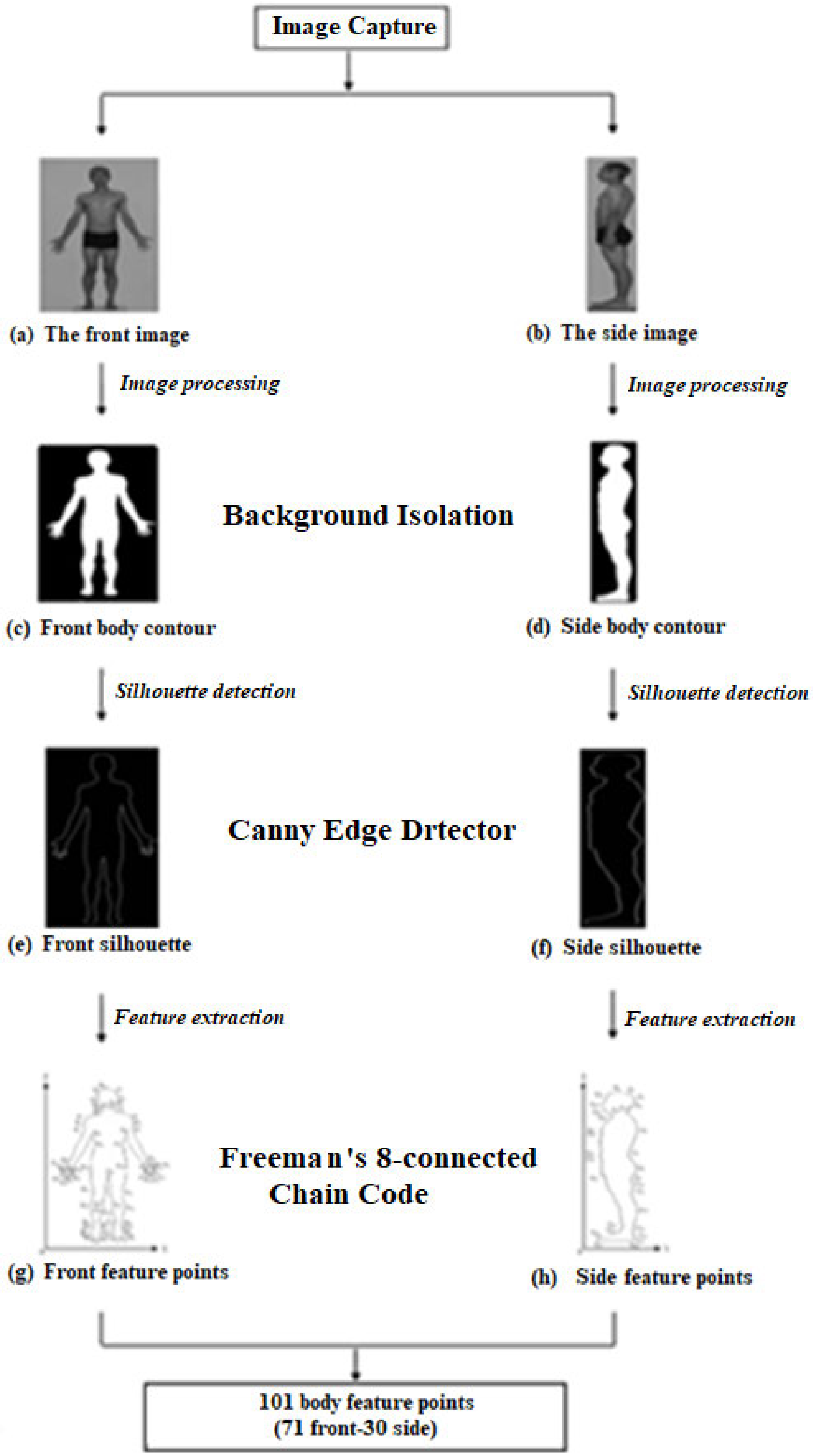


FIGURE 3. Automatic body feature extraction from front and side images.

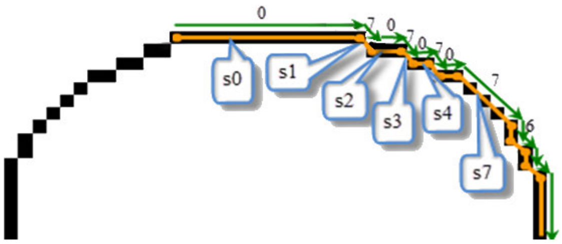


FIGURE 4. A part of line segments of head.

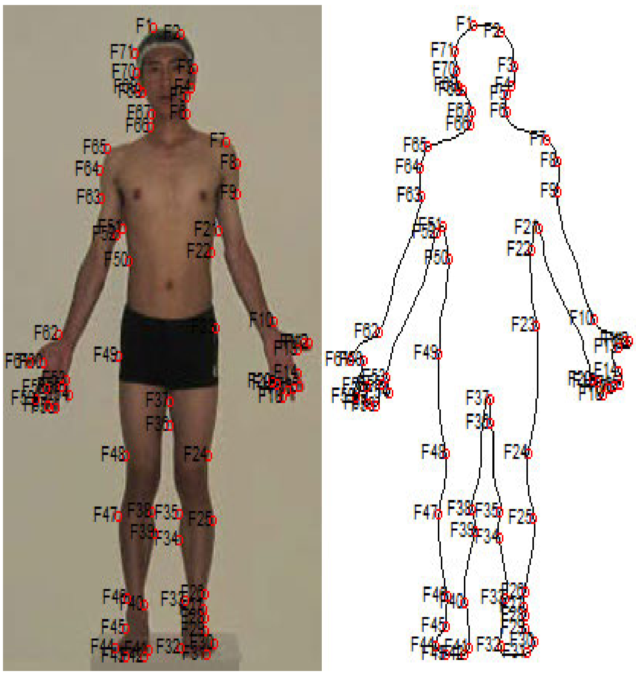


FIGURE 5. Body feature points for absolute difference method (marked with red circle) for front view.

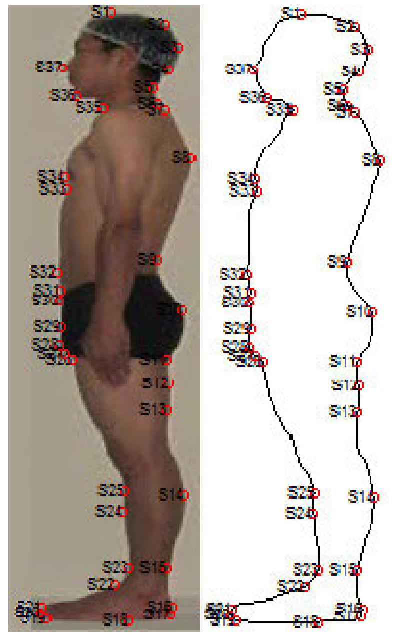


FIGURE 6. Body feature points for absolute difference method (marked with red circle) for side view.

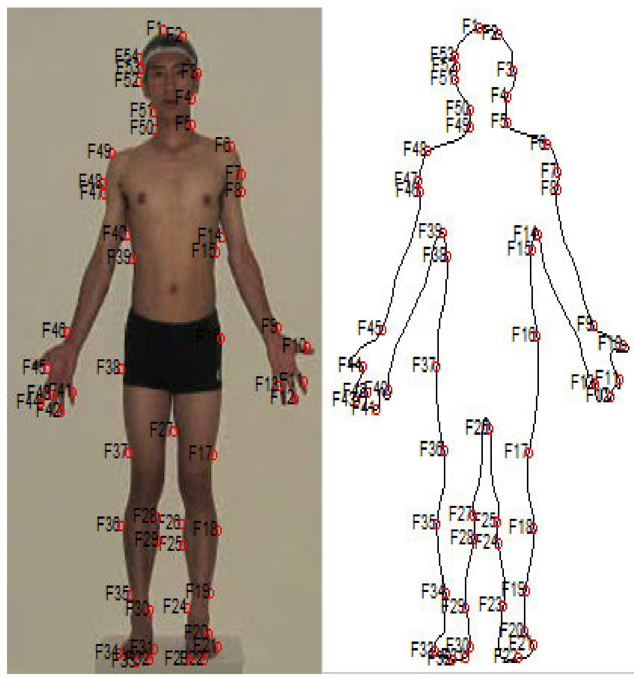


FIGURE 7. Body feature points for dilation method (marked with red circle) for front view.

sports, but it needs more attention in swimming sports. Wherefore, one of the main objectives of the presented article is the application of some AI techniques for swimming sports in order to make use of AI advantages. Particularly, canny filter and a fuzzy algorithm will be used to select promising junior swimmers. The proposed algorithms are verified using samples from Egyptian's children whose ages are around twelve years old. These algorithms are low-cost, easy used, and can be implanted in urban and rural areas.

Swimmer's performance depends on a multifactorial process that involves several scientific domains, such as the anthropometrics [8]–[13], hydrodynamics [14], [15], kinematics [16], [17] and energetics [18]–[20]. An important goal of swimming research is to identify the variables that predict the performance of young swimmers to enhance their talent [21]. Several authors [15], [16], [24] have determined many variables in these domains, that help to predict the talented swimmers. Anthropometric measurements can manually measure using direct instruments such as calipers and measuring tapes, but this process can be boring, time consuming and some human errors may cause reduced accuracy of measurement [25]. Image processing-based systems have the ability of collecting data rapidly without human intervention in a reproducible manner [23] and capable of providing anthropometric measurements with cost less, more accuracy and repeatability comparable with the manual anthropometric measurements [24]. However, camera resolution, camera calibration, landmark error, and modeling error cause some errors [25]. Therefore, the presented paper aims to develop

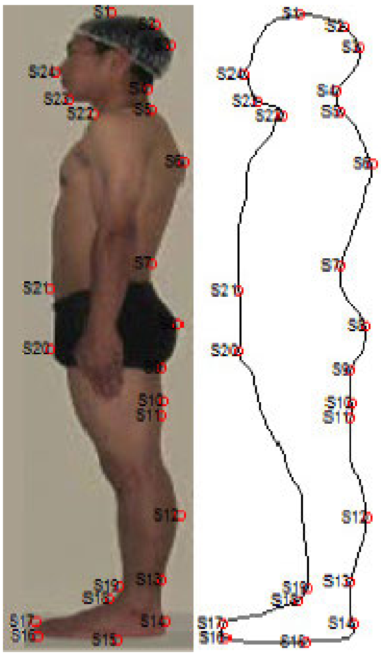


FIGURE 8. Body feature points for dilation method (marked with red circle) for side view.

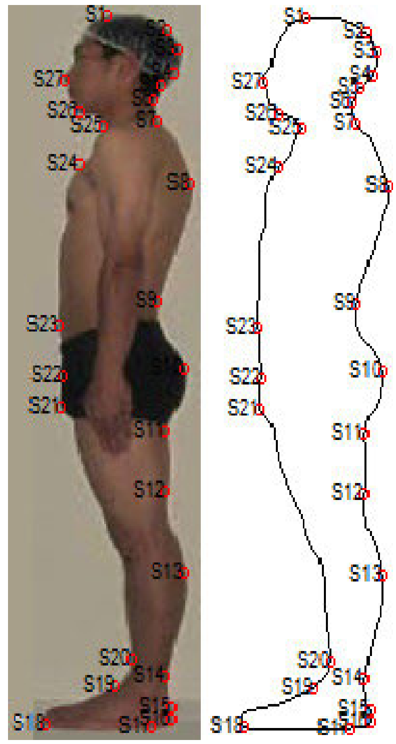


FIGURE 10. Body feature points for erosion method (marked with red circle) for side view.

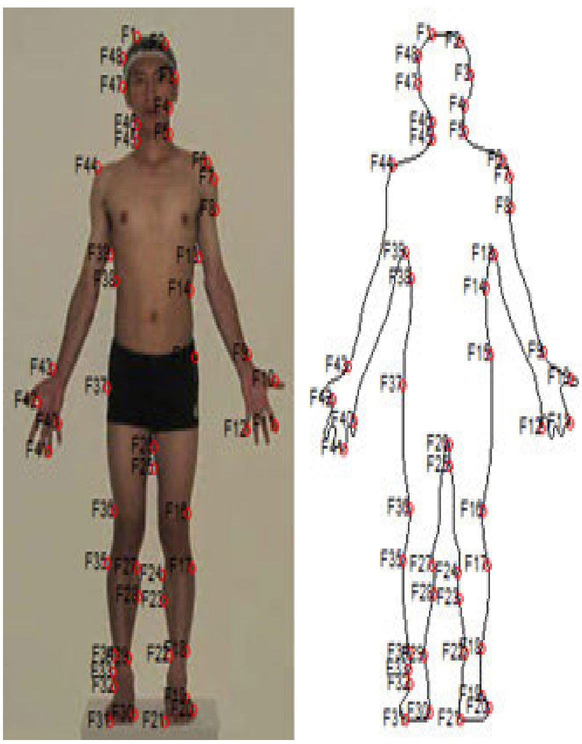


FIGURE 9. Body feature points for erosion method (marked with red circle) for front view.

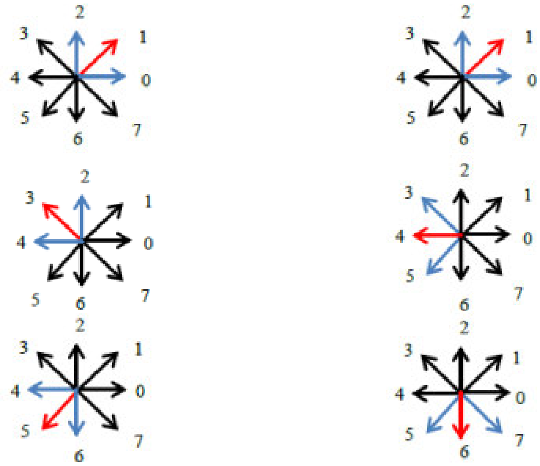
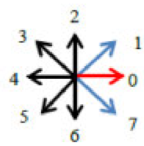
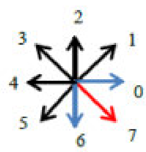
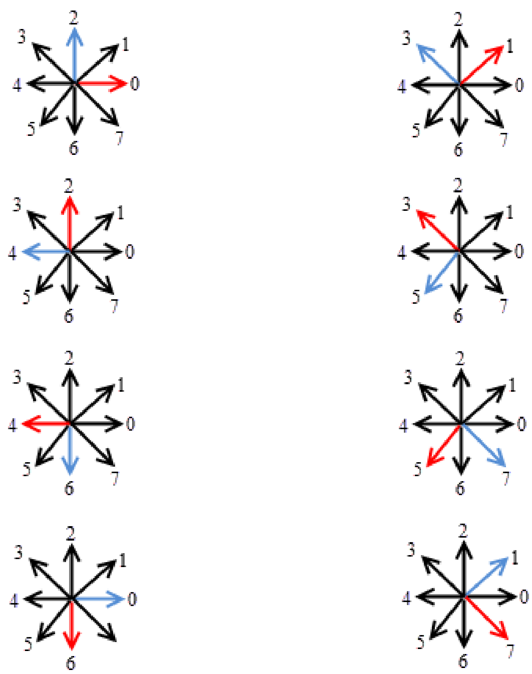
more efficient, simple, automated, and low-cost approach that use anthropometric measurements to select the promising junior swimmers. For these purposes two algorithms will be proposed. The first one is a Canny algorithm that uses 2D images, a front and side view, and then absolute difference method, dilation method and erosion method are used to detect the human contour. Canny edge detector and Freeman's 8-connected chain code are applied after the previous methods then human feature points are extracted automatically. Finally, the body measurements are calculated by the three different methods to recommend the best one. For body weight a digital weight scale is used to store it in a computer. The second algorithm is modified from the first algorithm by using fuzzy logic instead of Canny edge detector in that stage.

The motivation of the proposed work is to develop new techniques to select promising junior swimmers using some AI approaches. These techniques overcome some gaps in the previous researches, specially the missing of using AI in swimming sports, which is one of the main objectives of the presented article. Usually, AI approaches yield more precis results than traditional ones. Other objectives are developing easy-used and low-cost approach that suitable for low-income countries.

II. RELATED WORK

The successful management in swim training process is focused in measuring all the relevant skills and characteristics of swimmers that aiming to find the most influence characteristics to achieve top results [26]. The most anthropometric measurements that have a large effect on the swimmer's performance, and accordingly proper selection of junior swimmer, are the total lengths of stature, arm, hand, leg, weight, the normal chest parametric, chest parametric

TABLE 2. Rules applied in feature identification.

No	Formulas	Cases of line segment direction
1	d2-d1=-1 && d2-d3=1 d2-d1=1 && d2-d3=-1	
2	d2-d1=-1 && d2-d3=-7 d2-d1=-7 && d2-d3=-1	
3	d2-d1=1 && d2-d3=7 d2-d1=7 && d2-d3=1	
4	|d2-d1|=2	

Where $d1$, $d2$ and $d3$ denote the inclinations of the three adjacent segments.

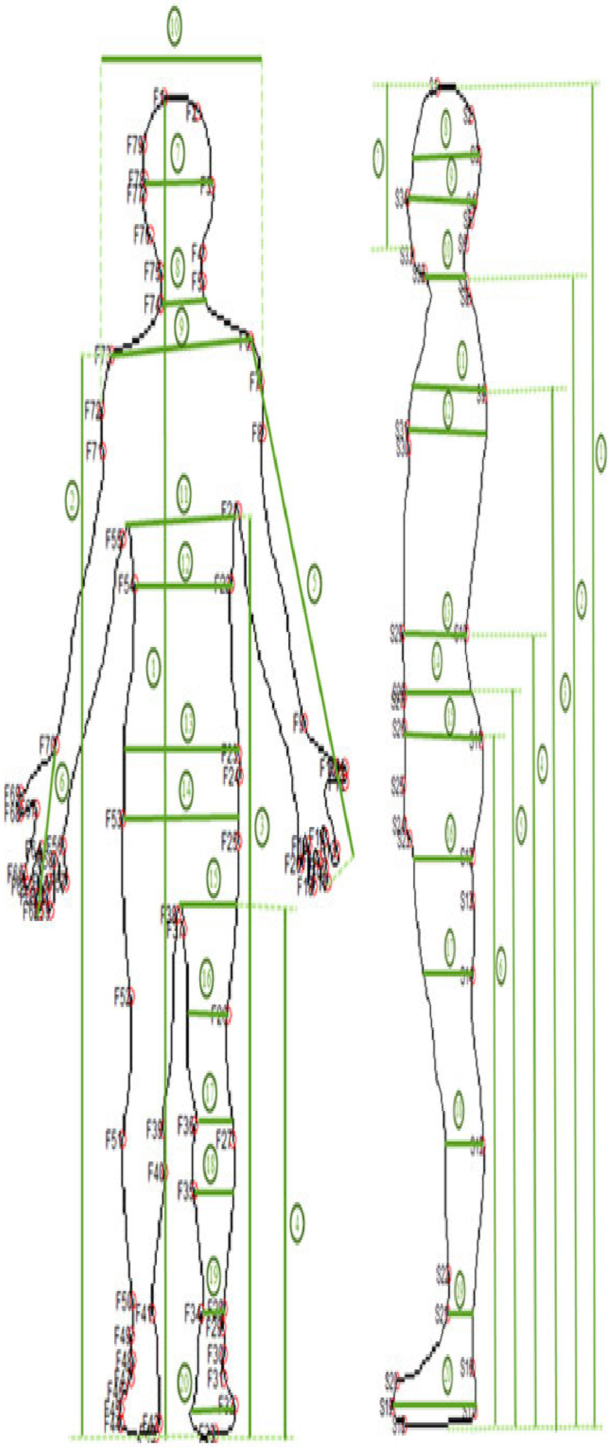


FIGURE 11. The front and side body measurements.

from maximum inhalation, chest width, shoulder width, and foot length [27], [28].

The manual measurement of those characteristics is tedious and may have human errors and therefore it is usually replaced by an automated, two-dimensional (2D) image processing technique [29], [30]. Based on these techniques

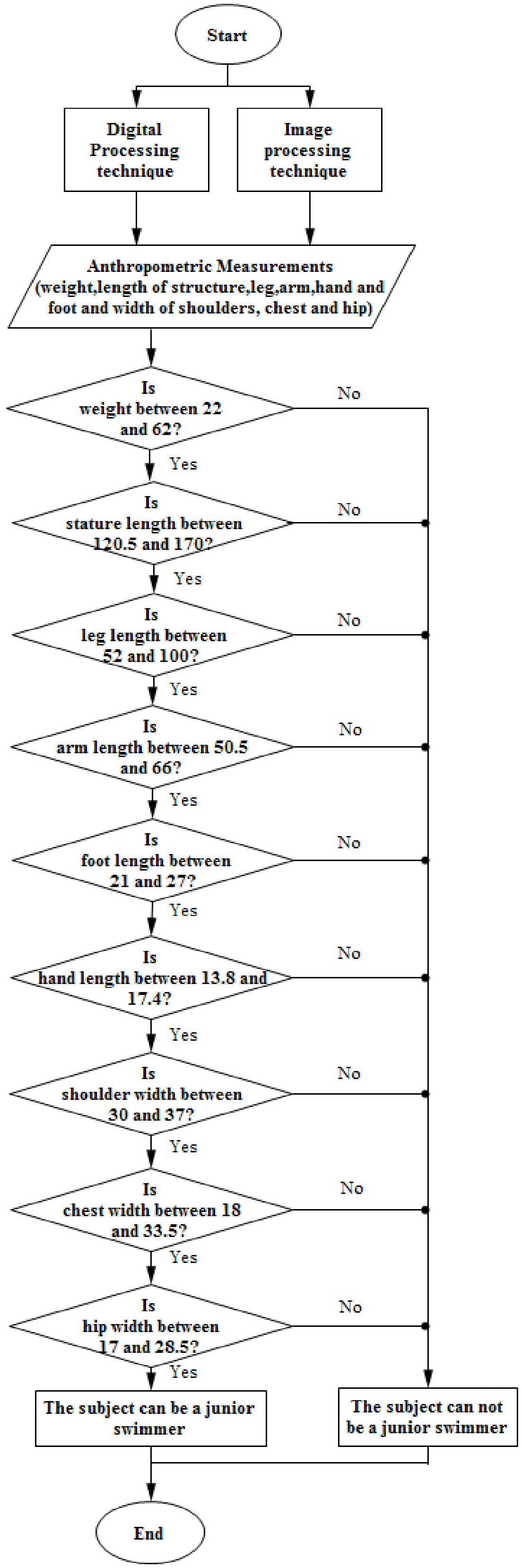


FIGURE 12. The system decision flowchart to select the junior swimmer.

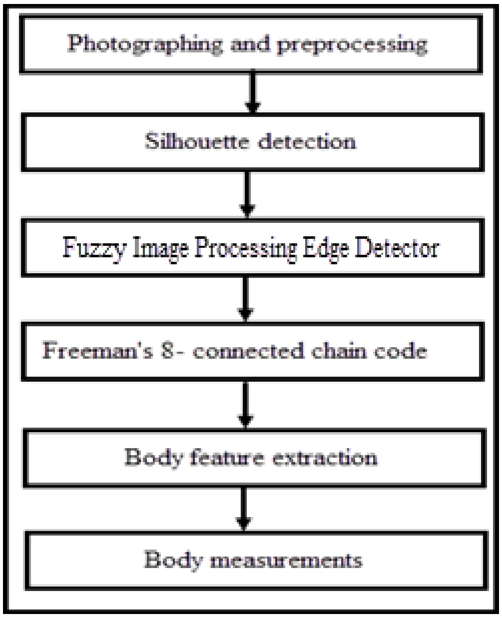


FIGURE 13. The fuzzy algorithm.

many algorithms have been developed to identify the features points from 25 body feature points (33 from the front view and 22 from the side view), 60 human feature points (38 from the front view and 22 from the side view), or 101 feature points from front and side images (71 from the front view and 30 from the side view), [32]–[34].

III. METHODOLOGY

A proposed system is designed to select a junior swimmer by determining the anthropometric measurements automatically. Lengths of stature, leg, foot, arm, hand, width of shoulders, hip, chest and weight are the anthropometric characteristics for swimming performance [26]–[28], [35]–[39]. Fig. 1. illustrates the block diagram of the proposed system.

The system structure is composed of two subsystems. The first one is designed to measure and store swimmer weight automatically using a digital weight scale. The second one is designed to extract and store human feature points, from front and side images, using two algorithms. The proper alignment of the associated points with the coordinates of the same horizontal height and plumb depth was taken into consideration [32].

The proposed methodology makes automatic anthropometric measurements from the front and side images for 36 human body dimensions by using 101 feature points, in addition to weight, as shown in Table 1. The swimming game needs 8 body dimensions only (the length of stature, leg, hand, arm food, and width of shoulders, chest, and hip) beside body weight to select the swimmer. The system obtains the anthropometric measurements for young swimmers, below 14 years, and compare these measurements with a database to select the promising junior swimmers. Since this system yields 36 human body dimensions, then it can also be applied

TABLE 3. The frontal body measurements.

Body Region	The Frontal Body Measurements	Code	Feature points	Ref.
Head	Stature	1	F3,F70	[11]
Shoulder	Shoulder height	2	F31,F65	[24]-[26]
Chest	Chest height	3	F21,F31	[24]-[26]
Crotch	Crotch height	4	F37,F31	[24]-[26]
Arm	Arm length	5	F7,F18	[24]-[26]
Hand	Hand length	6	F57,F62	[24]-[26]
Head	Head width	7	F3,F70	[11]
Neck	Neck width	8	F6,F67	[11]
Shoulder	Shoulder width	9	F7,F65	[11]
Shoulder	Shoulder (deltoid) width	10	F8,F64	[24]-[26]
Chest	Chest width	11	F21,F51	[11]
Abdomen	Abdomen width	12	F22,F50	[27]
Waist	Lower waist	13	F23	[24]-[26]
Hip	Hip width	14	F49	[11]
Thigh	Thigh width	15	F37	[11]
Thigh	Thigh width (most inside point)	16	F24	[13]
Knee	Knee width	17	F35	[11]
Shank	Shank width	18	F34	[11]
Ankle	Ankle width	19	F27,F33	[11]
Foot	Foot width	20	F30,F32	[11]

for some other games, that needs more features points than swimming game.

IV. ANTHROPOMETRIC MEASUREMENTS

The anthropometric measurements for junior swimmers are divided into body features measurements and body weight measurement. The computerized image-based approach replaced the traditional methods, that based on manual measurements, to avoid human errors and to reduce costs [31]. The automatic body features measurements require efficient approaches to extract feature points from more detailed information [32].

A. DIGITAL PROCESSING TECHNIQUE

The digital processing technique determines and stores young swimmers' weights in a computer. The system interfaces a digital weight scale with the computer.

B. IMAGE PROCESSING TECHNIQUE

The First Algorithm (Canny Algorithm):

The first algorithm, Canny algorithm, of image processing technique is illustrated in Fig. 2. This algorithm extracts the human feature points from a minimum number of images with front and side views automatically and obtain approximately the same feature point as shown in Fig. 3 [34].

TABLE 4. The side body measurements.

Body Region	The Side Body Measurements	Code	Feature points	Ref.
Head	Stature	1	S1,S17	[11]
Neck	Neck height	2	S35,S17	[24]-[26]
Shoulder	Shoulder height	3	S8,S17	[24]-[26]
Waist	Waist height	4	S9,S17	[24]-[26]
Abdomen	Abdomen height	5	S32,S17	[24]-[26]
Hip	Hip height	6	S10,S17	[24]-[26]
Head	mouth to vertex height	7	S1,S36	[24]-[26]
Head	Forehead to back of head depth	8	S3	[11]
Head	Pronasale to opisthocranion depth	9	S37,S4	[11]
Neck	Neck depth	10	S35,S6	[11]
Shoulder	Shoulder depth	11	S8	[24]-[26]
Chest	Chest depth	12	S34	[11]
Waist	Waist depth	13	S32,S9	[11]
Abdomen	Body depth	14	S30	[11]
Hip	Hip depth	15	S10,S29	[11]
Thigh	Thigh depth	16	S26,S11	[11]
Huckle	Huckle depth (most inside point)	17	S13	[24]
Shank	Shank depth	18	S14,S25	[11]
Ankle	Ankle depth	19	S23,S15	[11]
Foot	Foot depth	20	S16,S20	[11]

1) PHOTOGRAPHING AND PREPROCESSING

To apply the automatic body feature extraction technique some precaution must be taken; the subjects are lightly clothed and wear a headgear to reduce the influences of hair on the test result. In the frontal view, subjects are stood in front of a white wall with a standing posture, kept limbs straight, arms apart from the torso, legs apart from each other, fingers faced and forced open to the camera. The front and side images are resized into 309×211 pixels and 309×84 pixels, respectively.

2) AUTOMATIC SILHOUETTE DETECTION

The two stages that display the silhouette curves of body shape are human contour, and silhouette extraction.

a: HUMAN CONTOUR

In this phase the following three methods are used to obtain the best one among them, then this method is used to extract the shape of human contour.

Method (1): This method determines the absolute difference between the background and subject images to isolate the subject and then converted the RGB image to binary one, as described mathematically by the following equations [34].

$$\begin{vmatrix} Cij\,(R) \\ Cij\,(G) \\ Cij\,(B) \end{vmatrix} = \begin{vmatrix} Xij\,[R] - Yij\,[R] \\ Xij\,[G] - Yij\,[G] \\ Xij\,[B] - Yij\,[B] \end{vmatrix} \quad (i,j) \in \Omega \qquad (1)$$

TABLE 5. Anthropometric measurements of high performance junior swimmers.

Body parts	Range: Minimum	Range: Maximum
Stature length (cm)	120.5	170
Leg length (cm)	52	100
Hand length (cm)	13.8	17.4
Arm length (cm)	50.5	66
Foot length (cm)	21	27
Shoulder width (cm)	30	37
Chest width (cm)	18	33.5
Hip width (cm)	17	28.5
Weight (kg)	22	62

where Ω denote the fields of images, Xij and Yij represent the RGB color value of the current image pixel (i, j), and the background pixel (i, j) respectively.

$$D\,(ij) = d1xCij\,[R] + d2xCij\,[G] + d3xCij\,[B] \qquad (2)$$

where d1, d2 and d3 are the weighted value of Red, Green and Blue channels, respectively.

Method (2): It converts the subject image to binary one, creates a stature element, and then applies dilation morphological filter. The dilation of A by B is defined by the following equation:

$$A \oplus B = \{z|\,(B)\,z \cap A \neq \emptyset\} \qquad (3)$$

where ∅ is the empty set and B is the structuring element. The dilation of A by B is the set consisting of all the structuring element origin locations. The reflected and translated B overlaps at least one element of A.

Method (3): It converts the subject image to binary one then creates a structure element, and finally applies erosion morphological filter. The erosion of A by B is defined by:

$$A \ominus B = \{z|\,(B)\,z \subseteq \mathrm{A}\} \qquad (4)$$

b: SILHOUETTE EXTRACTION

The Canny edge detector [23] is applied to extract single pixel and closed contour curve that represent a silhouette of human body. That is depended on a multi-stage algorithm for edge detection, in addition to a smoothing filter for noise reduction [41].

3) AUTOMATIC FEATURE POINTS IDENTIFICATION

The feature points along body counter can be detected by tracing the shape of contour [42]. Freeman's 8- connected chain code algorithm is used to encode the shape of human silhouette [43], [44]. The chain code boundary curve is a series of connected line segments, as depicted in Fig. 4, starting from the upper left pixel of the image, and then tracing the silhouette curve clockwise from left to right and from top to bottom. The feature points will be detected from the adjacent segments using the specific rules listed in Table 2. This identification procedure is applied on the outputs of the three mentioned human contour methods, and hence it provides a

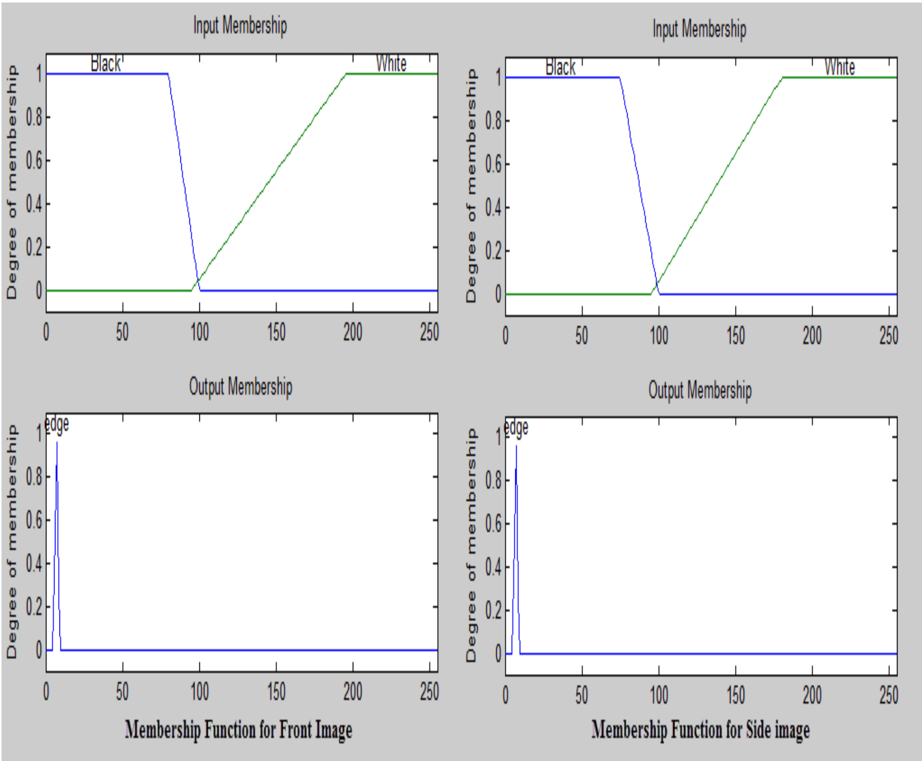


FIGURE 14. The fuzzy membership function of inputs and output for front and side images.

series of feature points for each method that identified from the front and side images.

Applying the absolute difference method, a total of 101 feature points with 71 feature points from the front view and 30 feature points from the side view can be extracted automatically as shown in Fig. 5 and Fig. 6., where F refers to the feature point from the front view and S refers to refers to the feature point. Using the dilation method, a total of 78 feature points with 54 feature points from the front view and 24 feature points from the side view can be extracted automatically as shown in Fig. 7 and Fig. 8. In case of applying the erosion method, a total of 75 feature points with 48 from the front view and 27 from the side view can be extracted automatically as shown in Fig. 9 and Fig. 10. side view can be extracted. automatically as shown in Fig. 9 and Fig. 10.

4) AUTOMATIC BODY MEASUREMENTS

The feature points obtained from the front and side images is used to obtain body dimensions. There are 36 body dimensions that can be extracted automatically as shown in Fig. 11 and Table2: 1 for stature, 13 for width, 12 for depth, 8 for heights and 2 for lengths. The 2D image-based body dimensions are listed in Table 3 and Table 4., and the code in tables refers to the number above the arrow in Fig. 11.

C. SYSTEM DATABASE

A system is designed to select Egyptian junior swimmers, so that the system database contains the anthropometric measurements of 144 high performance junior swimmers in Egypt [28], [49]. The database consists of stature length, leg length, hand length, arm length, foot length, shoulder width, chest width, hip width, and weight. Principle component analysis of data clustering showed that the proper age for ameliorating junior swimmers' talent should below 16 years [50]. Our choice coincides with this argument, since the ages of the selected 144 junior swimmers were under 12 years old. The maximum and the minimum values of the selected anthropometric measurements for the junior swimmer were extracted as shown in Table5.

D. SYSTEM DECISION

A system is designed in order to be capable to select promising junior swimmers by comparing the anthropometric measurements of the candidate with that ones in the data base system. Fig. 12 illustrates this system, where information is entered from digital processing and image processing techniques and the decision is achieved according the given 9 features.

E. THE SECOND ALGORITHM (FUZZY ALGORITHM)

The second algorithm is a modification of the first algorithm, using fuzzy logic instead of canny filter in the edge detection phase. Fig. 13 illustrates the proposed fuzzy algorithm, which concerned mainly with the automatic silhouette detection stage,

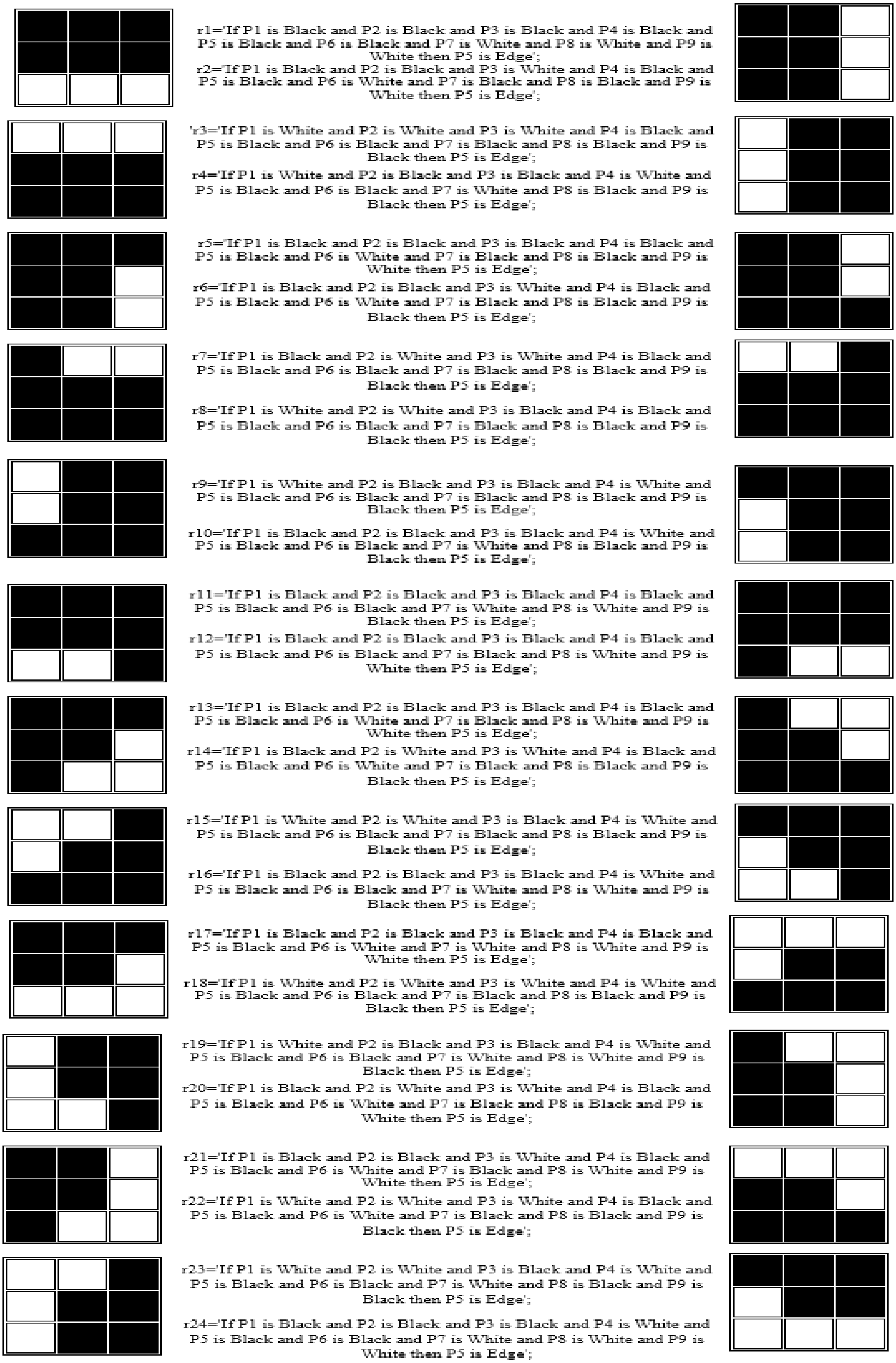


FIGURE 15. Fuzzy rules.

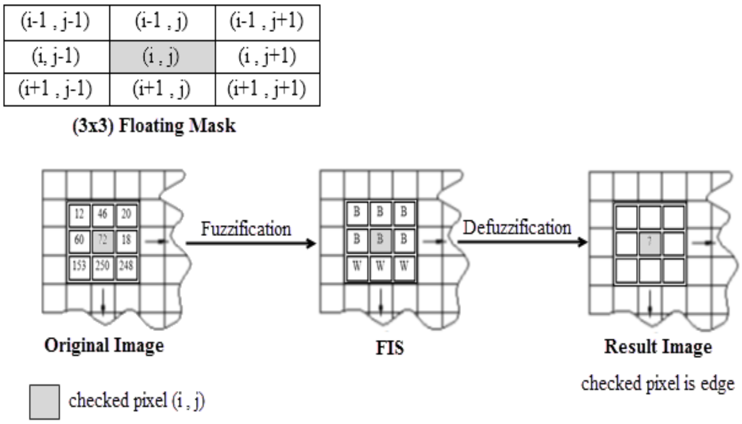


FIGURE 16. Steps of fuzzy processing.

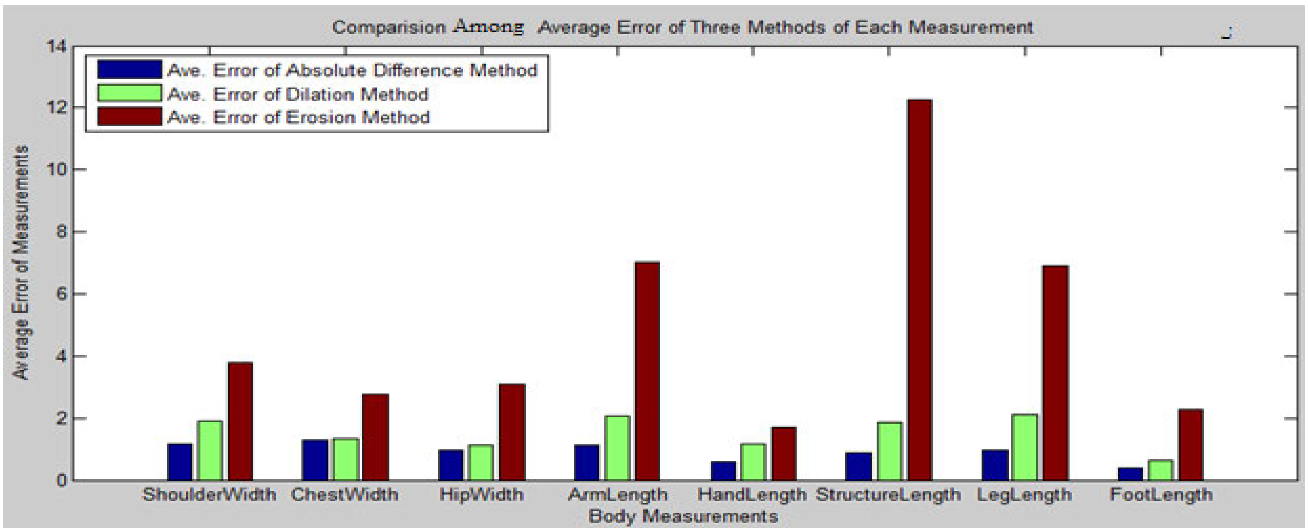


FIGURE 17. Average error comparison between the first algorithm and the fully vision-based system.

1) AUTOMATIC SILHOUETTE DETECTION

Principal morphological operations consist two phases that display the silhouette curves of body shape, namely, human counter and Silhouette extraction.

a: HUMAN CONTOUR

In this phase the shape of human counter is extracted by determining the absolute difference between the background and subject images to isolate the subject and then convert the RGB image to a gray scale one.

b: SILHOUETTE EXTRACTION

This phase applies the fuzzy image processing edge detector to extract single pixel and the closed counter curve that represents a silhouette of human body. Fuzzy image processing has three main stages: image fuzzification, modification of membership values and image defuzzification. The image are transformed from gray-level plane to the membership plane (fuzzification) and appropriate fuzzy techniques are used to modify the membership values. These techniques may be a fuzzy clustering, a fuzzy rule-based approach, or a fuzzy integration approach and so on [53]–[57].

The gray level presents each pixel in 8-bit that ranged between 0 and 255. The created fuzzy sets represent each variable's intensities. These sets are associated with the linguistic variables (Black, White and Edge). The trapezoidal membership functions represent inputs and triangular ones represent outputs, as shown in Fig. 14. The fuzzy rules depend on the eight neighbours gray level pixel's weight taht depend on degrees of blacks or whites. The floating 3×3 mask are used to represent the eight neighbours of each pixel [53]. The 24 rules, that shown in Fig. 15, are used to extract the silhouette curve.

The first four rules represent the vertical and horizontal lines around the the mask center pixel, if the grays represented in one line is white and the remains grays are black then

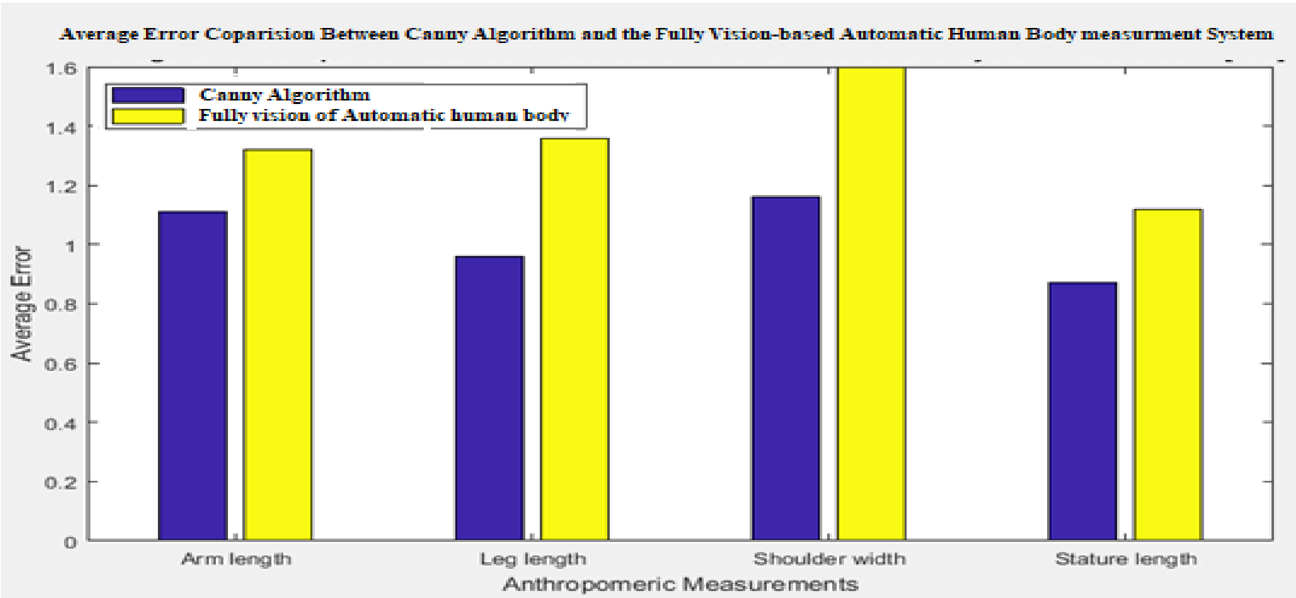


FIGURE 18. The comparison among average error of the absolute difference method, dilation method and erosion method.

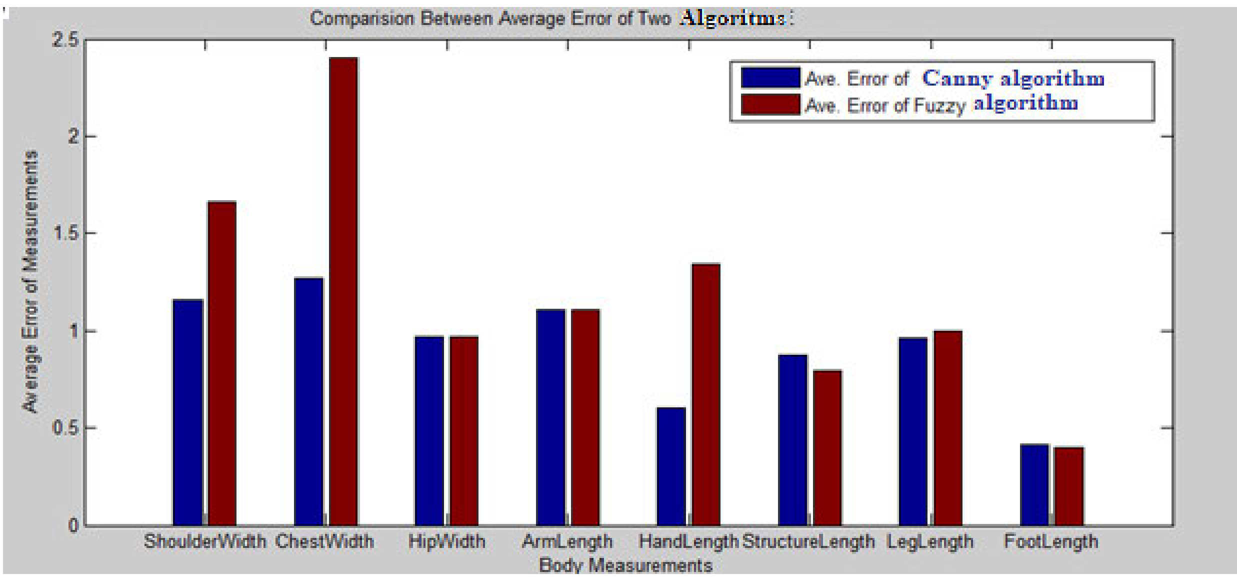


FIGURE 19. Comparison between average error of the canny algorithm and fuzzy algorithm.

the checked pixel represent an edge. The second eight rules show that if the weights of the six sequential pixels are degree of blacks and the weights of the remain neighbors are the degree of whites, then the center pixel represented an edge. The third four rules depict that if the weights of three corner pixels are degree of white and the weights of remain pixels are degree of black, then the center pixel represented an edge. The remainder eight rules are related to the weight of one half of neighbour pixels, if it is degree of white and the other is a degree of black, then the center pixel represented an edge.

From the side of the fuzzy construction, the input grays range from 0 to 255 gray intensity, and according to the desired rules the gray level is converted to the values of the membership functions as shown in Fig.16. The output of the fuzzy inference systems (FIS) according to the defuzzification is presented again to the values from 0- 255 then the black, white and edge are detected. From the experience of the tested images, the best result achieved when membership functions for black variable declared as [0 0 80 100] for front images and [0 0 75 100] for the side images and for white variable declared as [95 195 256 256] for front images and [95180 256 256] for side images.

V. EXPERIMENTAL RESULTS

The implemented experiments in this article used the SONY Cyber-shot DSC-W710 color digital camera. The camera was

TABLE 6. Result of the body measurement system from front view using three methods.

No		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
SW (cm)	M	27.5	28	32	31	33	31	31	28	26	32	30	29	28	33	31
	M1	25.9	27.8	29.3	28.8	34	29.3	30.4	26.8	24.8	30.5	29.1	28.6	27.2	32.5	30.1
	M2	25.2	24.7	27.5	28.5	32.9	28.3	30.9	25.2	24.3	29.4	27.1	27.1	28	32.2	30.8
	M3	22.7	25.3	26.6	26.1	31.3	27	28.9	24.6	22.2	27.3	25.6	25.2	25.2	27.7	28.1
CW (cm)	M	23	23.5	24	28	30	26	28	26	22	25.5	27.5	25	26	31	29
	M1	23.9	25.4	26.3	28.8	29.3	24.2	26.3	24.7	23.4	26.3	26.7	23.9	25.3	29.1	28.2
	M2	22.4	24.3	25.2	28.9	28.8	25.2	32.4	24.7	22.4	26.1	25.2	22.9	24.7	30.3	27.5
	M3	21	22.7	23.1	25.3	27.4	23.1	25	23.1	20.5	24.8	23.1	21	22.3	26	24.8
HW (cm)	M	29	25.5	26	34	34	29	31	29	25	26.5	26	28	29	32	30
	M1	28.2	28.3	27.8	35.2	35.2	29.3	31.4	28.8	25.8	28.6	26.7	26.7	29.6	32.5	31
	M2	27.5	28	27.5	34.5	34.5	29.9	32.4	29.9	26.1	28.9	27.1	27.5	29.9	32.2	31.3
	M3	24.8	24	23.1	30	30	26.5	28.4	26	21.8	27.7	22.7	23.1	25.2	28.1	26.5
AL (cm)	M	56	59	62	58.5	66	65	71	60	62	66	61	63	62	67	67
	M1	55.1	57.1	60.2	57.4	64.7	63.7	71	59.4	60.6	65.8	59.9	61.6	61.2	66.1	65.2
	M2	52.1	56.1	58.4	54.1	65.5	64.4	70.6	61.8	60.2	64.7	59.5	61.4	60.2	64.9	64.4
	M3	49.4	51.4	53.1	51.2	57.6	58.6	65.7	55.3	54.3	62.5	53.7	54.9	53.6	61	57.9
HL (cm)	M	14	16.5	16	16	16	17	19	17	15	16	17	17.5	17.5	17.5	18
	M1	14.8	15.3	16.5	14.4	15.9	16.1	19.3	17.3	14.3	16.5	16	17.7	17.1	17.1	17.8
	M2	14.7	14	16.8	14	17.2	16.3	17.1	17	14.1	16.8	17.6	16.8	16.8	15.9	15.8
	M3	13.4	14.4	14.3	14.8	14.5	13.9	18.9	17.3	12	16.8	14.4	13.3	14.9	17.2	16.5

Where (SW) shoulder width, (CW) chest width, (HW) hip width, (AL) arm length, (HL) hand length, (M) manual, (M1) Absolute difference method, (M2) Dilation method, (M3) Erosion method.

TABLE 7. Statistical analysis of body measurements from front view for manual and three mentioned methods.

No	Body parts	Shoulder width (cm)	Chest width (cm)	Hip width (cm)	Arm length (cm)	Hand length (cm)
Mean	Manual	30	26.3	28.4	63	16.7
	Absolute Difference	29	26.1	29.2	61.9	16.4
	Dilation	28.1	26.1	29.4	61.2	16.1
	Erosion	26.3	23.6	25.5	56	15.1
Std. dev.	Manual	2.2	2.6	2.9	4	1.2
	Absolute Difference	2.4	2	2.8	4.2	1.4
	Dilation	2.7	2.9	2.8	4.8	1.3
	Erosion	2.3	2	2.8	4.5	1.8
Corr. Coef.	Absolute Difference	0.9291	0.8435	0.9422	0.9919	0.8580
	Dilation	0.8633	0.8207	0.9587	0.9545	0.5083
	Erosion	0.8678	0.8576	0.8811	0.9396	0.6491
Average error (cm)	Absolute Difference	1.16	1.27	0.97	1.11	0.6
	Dilation	1.89	1.34	1.12	2.05	1.15
	Erosion	3.77	2.75	3.09	7.03	1.71
Max. error (cm)	Absolute Difference	2.7	2.4	2.8	1.9	1.6
	Dilation	4.5	4.4	2.5	4.4	2.5
	Erosion	5.4	5	4.9	9.1	4.2

located at 4.5m distance and 1.1m height from the object, with white background. The camera was calibrated by the camera calibration technique [51]. The captured images have a resolution of 2304 x 1728 pixels, but it was reduced to

TABLE 8. Result of the body measurement system from side view using three methods.

No		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
SL (cm)	M	132	142	142	139.5	150	148	161	141	142	158	138.5	145	144	155	152
	M1	132.3	142.6	143.6	140.9	151	146.4	160.7	141.8	139.5	158	139	143.2	143.7	154.9	151.7
	M2	129.2	139.6	139.6	137.6	152.1	147	162.5	142.9	138.6	156.8	138.1	141.7	144.3	153.2	150.6
	M3	119.3	129	132.9	127.6	137.2	133.5	150.3	133	126.5	143.2	125.5	129.3	134.6	143.7	140.8
LL (cm)	M	76	83	86	86	93	91	99	84	87	98	85	85.5	87	97	94
	M1	75.1	81	84.8	87.5	93.6	91.3	99.9	82.1	88	97.6	86.4	85.9	85.9	97.1	93.3
	M2	71.9	79.2	82.3	83.9	91.9	90.1	101	82.7	86	95.4	83.4	83.9	85.5	94.8	92.2
	M3	69.9	75.5	77.9	81.3	86.9	82.2	93.7	77	81.9	87.2	78.6	79.5	80.5	89.6	86.7
FL (cm)	M	19	23	23.5	23	24	23	26	23	22	25	23	23	24.5	26	26
	M1	19	23.4	23.9	23.9	24.1	22.5	26.7	23	22	25.4	22	23	24.9	26.9	26.4
	M2	18.7	22.4	22.9	22.9	24.6	23	26.7	23	21	24.3	21	21.9	23.8	26.1	25.2
	M3	15.9	19.7	23.6	20.6	22	20.6	27.4	25.9	18	21.4	18.4	19.7	24.4	26.1	25.3
W (kg)		22.9	30.9	34.5	48.6	42.8	34.4	42.4	30.8	33.6	41.6	31.7	32.3	36	46.6	46.7

Where (SL) stature length, (LL) leg length, (FL) foot length, (w) weight, (M) manual, (M1) Absolute difference method, (M2) Dilation method, (M3) Erosion method.

TABLE 9. Statistical analysis of body measurements from side view for manual and three mentioned methods.

No	Body parts	Stature Length (cm)	Leg length (cm)	Foot length (cm)	Weight (kg)
Mean	Manual	146	88.8	23.6	37.1
	Absolute Difference	146	88.6	23.8	
	Dilation	144.9	86.9	23.2	
	Erosion	133.8	81.9	21.9	
Std. dev.	Manual	7.9	6.4	1.8	7.3
	Absolute Difference	7.8	6.8	2.1	
	Dilation	8.7	7.3	2.1	
	Erosion	8.2	6.1	3.4	
Corr. Coef.	Absolute Difference	0.9891	0.9873	0.9770	-
	Dilation	0.9808	0.9860	0.9462	
	Erosion	0.9584	0.9702	0.8186	
Average error (cm)	Absolute Difference	0.87	0.96	0.41	-
	Dilation	1.85	2.09	0.62	
	Erosion	12.24	6.89	2.27	
Max. error (cm)	Absolute Difference	2.5	2	1	-
	Dilation	3.4	4.1	2	
	Erosion	15.7	10.8	4.6	

211×309 pixels and 84×309 pixels respectively, to reduce the data processing time.

A. THE CANNY ALGORITHM

Fifteen children aged between 9-10 years were tested, according to the eight anthropometric measurements and the measured weight [26]–[28], [35]–[38]. Tables 6 and 8 show the differences between manual measurements and the automatic system measurements, from the front and side images, using the previously three mentioned methods. Tables 7 and 9 illustrate the mean, standard deviation, correlation coefficients, maximum, and average error between manual measurements and the image processing methods.

Body measures', from front view for stature, leg, and foot lengths, showed that erosion method yielded the best results for mean value, while absolute difference yielded the best correlation coefficient, minimum absolute errors and average errors (Table 7). Results were the same using side view

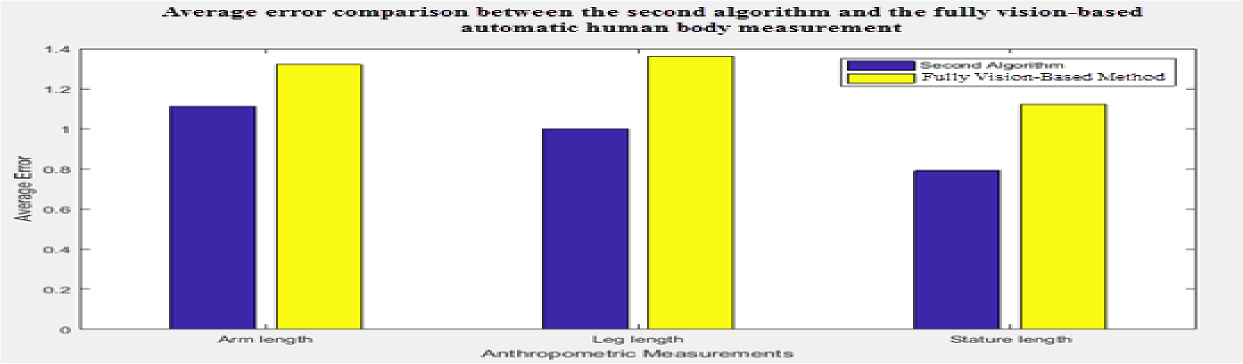


FIGURE 20. Average error comparison between the fuzzy algorithm and the fully vision-based automatic human body measurement method.

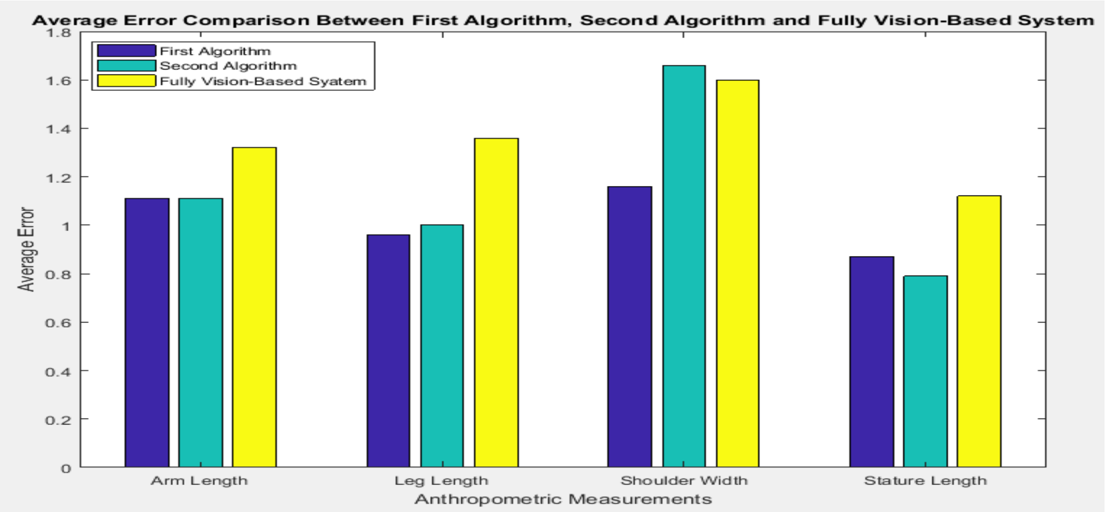


FIGURE 21. The comparison among canny algorithm, fuzzy algorithm and fully vision-based system.

TABLE 10. The average error comparison between the absolute difference method and method illustrated in [31].

Body Parts	Average Error (cm)		Enhancement %
	Fully Vision-based system	Absolute Different Method	
Stature Length	1.12	0.87	22.23%
Arm Length	1.32	1.11	15.9%
Leg Length	1.36	0.96	29.41%
Shoulder Width	1.6	1.16	27.5%
Foot Length	0.04	0.41	-90.24%

TABLE 11. Anthropometric measurements of high performance junior swimmers included average error.

Body parts	Range	
	Minimum	Maximum
Stature length (cm)	119.6	171.9
Leg length (cm)	51	101
Hand length (cm)	13.2	18
Arm length (cm)	49.4	67.1
Foot length (cm)	20.6	27.4
Shoulder width (cm)	28.8	38.2
Chest width (cm)	16.7	34.8
Hip width (cm)	16.3	29.5
Weight (kg)	22	62

data (Table 9). A comparison between the average errors of the image processing methods for all measurements is illustrated in Fig. 17., which shows that the absolute difference method has least average error for the length of stature, arm, hand, leg and foot and width of shoulders, chest and hip. Therefore, this method is recommended to be used in the presented study.

Comparing the average errors of the common anthropometric measurements (stature length, arm length, leg length, foot length and shoulder width), that obtained by using the first algorithm in the recommended method with the fully vision-based automatic human body measurement system [52], shows that all common anthropometric measurements, except the foot length, have fewer average errors than the fully vision-based automatic human body measurement system as illustrated in Fig. 18.

Table 10 illustrated the percentage of enhancement of these measurements using the proposed method for all features,

TABLE 12. Result of the body measurement system from front view using three methods.

No	Body parts	Shoulder Width (cm)	Chest width (cm)	Hip width (cm)	Arm length (cm)	Hand length (cm)
1	Manual	27.5	22	24	56	14
	Canny	27.6	25.4	25.4	55.1	14.9
	FIS	25.7	22.9	24.3	54.7	16.1
2	Manual	28	23.5	25.5	59	16.5
	Canny	27.8	25.4	28.3	57.1	15.3
	FIS	26.6	25.2	27.5	58.6	16.1
3	Manual	32	24	26	62	16
	Canny	29.3	26.3	27.8	60.2	16.5
	FIS	28	23.3	27.1	60.6	18.3
4	Manual	31	28	34	58.5	16
	Canny	28.8	28.8	35.2	57.4	14.4
	FIS	28.9	27.5	34.1	56	16
5	Manual	33	30	31	66	16
	Canny	34	29.3	31.4	64.7	15.9
	FIS	32.4	28.8	31.4	65.1	18.3
6	Manual	31	26	29	65	17
	Canny	29.3	24.2	29.3	63.7	16.1
	FIS	28.8	24.8	29.3	63.2	16.9
7	Manual	31	28	31	71	19
	Canny	30.4	26.3	31.4	71	19.3
	FIS	29.3	27.8	31.4	72.2	20.5
8	Manual	28	26	29	60	17
	Canny	26.8	24.7	28.8	59.4	17.3
	FIS	23.8	24.3	28.8	62.3	17.7
9	Manual	26	22	25	62	15
	Canny	24.8	23.4	25.8	60.6	14.3
	FIS	24.3	23.4	26.3	61.4	14.6
10	Manual	32	25.5	26.5	66	16
	Canny	30.5	26.3	28.6	65.8	16.5
	FIS	30.5	26.3	29.6	65.8	16.7
11	Manual	30	27.5	26	61	17
	Canny	29.1	26.7	26.7	59.9	16
	FIS	29.6	25.8	27.2	60.2	16.8
12	Manual	29	25	28	63	17.5
	Canny	28.6	23.9	26.7	61.6	17.7
	FIS	27.7	23.4	27.7	62.9	18.2
13	Manual	28	26	29	62	17.5
	Canny	27.2	25.3	29.6	61.2	17.1
	FIS	28.6	25.3	30.1	61.3	18
14	Manual	33	31	32	67	17.5
	Canny	32.5	29.1	32.5	66.1	17.1
	FIS	32.5	29.1	33.4	65	12.1
15	Manual	31	29	30	67	18
	Canny	30.1	28.2	31	65.2	17.8
	FIS	30.1	28.2	31.5	66.5	16.6
Mean	Manual	30	26.3	28.4	63	16.7
	Canny	29	26.1	29.2	61.9	16.4
	FIS	28.5	27.2	29.3	62.4	17
Std. dev.	Manual	3.2	2.2	3.7	3.1	1
	Canny	2.3	2.2	4	3	1
	FIS	2.6	6.6	2.7	4.4	2
Cor. Coef.	Canny	0.9291	0.8435	0.9422	0.9919	0.8580
	FIS	0.8707	0.5334	0.9453	0.9621	0.3474
Aver. error (cm)	Canny	1.16	1.27	0.97	1.11	0.6
	FIS	1.66	2.4	0.97	1.11	1.34
Max. error (cm)	Canny	2.7	2.4	2.8	1.9	1.6
	FIS	4.2	21.1	3.1	2.5	5.4

TABLE 13. Result of the body measurement system from side view using three methods and weight.

No	Body parts	Stature (cm)	Leg length (cm)	Foot length (cm)	weight (kg)
1	Manual	132	76	19	22.9
	Canny	132.3	75.1	19	
	FIS	132.1	74.8	19.1	
2	Manual	142	83	23	30.9
	Canny	142.6	81	23.4	
	FIS	142.1	81.1	23.4	
3	Manual	142	86	23.5	34.5
	Canny	143.6	84.8	23.9	
	FIS	143.2	84.9	24.8	
4	Manual	139.5	86	23	48.6
	Canny	140.9	87.5	23.9	
	FIS	140.5	87	22.9	
5	Manual	150	93	24	42.8
	Canny	151	93.6	24.1	
	FIS	150.4	94.6	24.3	
6	Manual	148	91	23	34.4
	Canny	146.4	91.3	22.5	
	FIS	145.9	92.4	22.8	
7	Manual	161	99	26	42.4
	Canny	160.7	99.9	26.7	
	FIS	161.1	99.7	26.3	
8	Manual	141	84	23	30.8
	Canny	141.8	82.1	23	
	FIS	141.9	82.8	23.3	
9	Manual	142	87	22	33.6
	Canny	139.5	88	22	
	FIS	140.2	89.6	22	
10	Manual	158	98	25	41.6
	Canny	158	97.6	25.4	
	FIS	157.9	98.5	25.8	
11	Manual	138.5	85	23	31.7
	Canny	139	86.4	22	
	FIS	139.1	85.5	22.4	
12	Manual	145	85.5	23	32.3
	Canny	143.2	85.9	23	
	FIS	143.3	84.4	23.4	
13	Manual	143.7	85.9	24.9	36
	Canny	144.3	85.5	23.8	
	FIS	144.9	87.5	24.8	
14	Manual	155	97	26	46.6
	Canny	154.9	97.1	26.9	
	FIS	154.8	97.4	26.7	
15	Manual	152	94	26	46.7
	Canny	151.7	93.3	26.4	
	FIS	152.7	94.8	25.8	
Mean	Manual	146	88.8	23.6	37.1
	Canny	146	88.6	23.8	
	FIS	146	88.9	23.9	
Std. dev.	Manual	7.9	6.4	1.8	7.3
	Canny	7.8	6.8	2.1	
	FIS	7.9	7.1	2	
Corr. Coef.	Canny	0.9891	0.9873	0.9770	-
	FIS	0.9910	0.9922	0.9736	
Average error (cm)	Canny	0.87	0.96	0.41	-
	FIS	0.79	1	0.4	
Max. error (cm)	Canny	2.5	2	1	-
	FIS	2.1	1.9	1.3	

except foot length. This big difference between the average errors of the foot length reasoned to the use of special devices in the fully vision-based automatic human body measurement system.

Based on tables 7, 9 and 3, Table 11 is obtained which indicates that applying the first algorithm, 4 junior swimmers among 15 ones will be promising ones.

TABLE 14. The comparison between the fuzzy algorithm and fully vision-based automatic human body measurement method.

Body Parts	Average Error		Enhancement %
	Fully Vision-Based Method	The Fuzzy Algorithm	
Stature Length	1.12	0.79	29.46%
Arm Length	1.32	1.11	15.9%
Leg Length	1.36	1.0	26.47%

B. THE FUZZY ALGORITHM

Tables 12 and 13 show the manual measurements and the automatic system measurements from the front and side images of the two algorithms, for the 15 tested junior swimmers. They also include statistical analysis in terms of mean, stander deviation correlation coefficients, average error, and maximum error. Body measures' analysis, from front view, using fuzzy concepts (FIS), yielded little enhancement, based on mean errors, for shoulder width only; but canny method is better for widths of chest and hip, and also for lengths of arm and hand. Canny method is better, based on standard deviation, correlation coefficients, average errors, and minimum errors, for all these anthropometric characteristics (Table 12). Body measures' analysis, from front side view, using FIS yielded the same results, based on mean errors, as canny method for all anthropometric characteristics. FIS method gave little enhanced results, based on average and minimum errors, correlation coefficients, and standard deviation, more than canny method (Table 13).

Fig. 19 show a comparison, based on average error, between the two algorithms. This figure indicates that the Fuzzy algorithm enhances the average error in the structure length and foot length.

Table 14 and Fig. 20 show a comparison between the proposed Fuzzy method and the fully vision based one [52]. It's evident that the proposed Fuzzy method yielded less average error for stature length, arm length and leg length.

Table 15 and Fig. 21 show a comparison between the Canny algorithm, Fuzzy algorithm and the fully vision-based automatic human body measurement system.

In light of the results of listed in Table 15, it's obvious that:

- The Canny algorithm has the best results for leg length, and shoulder width, and also it has the same result as the Fuzzy algorithm for arm length.
- The Fuzzy algorithm has the best result only for Stature Length.

The previous results were obtained using two dimensional techniques rather than three dimensional one. Moreover, inexpensive color digital camera was used and the resolution was reduced to 211 × 309 pixels and 84 × 309 pixels respectively, instead of 2304 × 1728 pixels, to reduce the data processing time. These factors imposed some limitations on selection accuracy, but these factors are necessary to achieve a high-speed and a low-cost approach that is suitable as a preliminary selection step, and also appropriate for use in low-income countries.

TABLE 15. The comparison among the canny algorithm, the fuzzy algorithm and the fully vision-based system.

Body Parts	Fully Vision-Based Method	Canny Method		Fuzzy Method	
	Average Error	Average Error	Enhancement%	Average Error	Enhancement%
Stature Length	1.12	0.87	22.23%	0.79	29.46%
Arm Length	1.32	1.11	15.9%	1.11	15.9%
Leg Length	1.36	0.96	29.41%	1.0	26.47%
Shoulder width	1.6	1.16	27.5%	1.66	-3.75%

VI. CONCLUSION

The two proposed algorithms, Canny and Fuzzy algorithms, built a system that extracts 101 feature points automatically from front and side images of a human body. These feature points are capable of measuring 36 body measurements. Swimming game, that addressed in this paper, needs 8 body dimensions only from those 36 ones. Thus, the system is not limited to the swimming sports, but may be applied in many other sports according to their anthropometric measurements. The 8 body measurements and weight are used to select the junior swimmers that meets the best performance criteria System validation was applied to 15 children whose ages were around 12 years old.

The Canny algorithm addressed three different methods; absolute difference, dilation and erosion. The absolute difference method achieved the best results; therefore, it's recommended to use it for the two algorithms. The system selected 4 promising junior swimmers from the15 ones. Moreover, and based on the average errors criteria, the first algorithm has the ability to enhance the results that has been obtained using fully vision-based automatic human body measurement system by the following percentages: stature length 22.23%, arm length 15.9%, leg length with 29.41% and shoulder width 27.5%.

The fuzzy algorithm yielded the best result for Stature Length, whereas the Canny algorithm gave the best results for Leg Length, and Shoulder width.

The proposed system, that developed in this paper, opens a new era in Egypt sports. The presented automated system has the ability to select juniors' players who have strong chance to success. Moreover, it reduces the workload, energy, required time and cost to reach high player performance.

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