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A Hybrid Soft-computing Method for Image Analysis of Digital Plantar Scanners

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ABSTRACT

Digital foot scanners have been developed in recent years to yield anthropometrists digital image of insole with pressure distribution and anthropometric information. In this paper, a hybrid algorithm containing gray level spatial correlation (GLSC) histogram and Shanbag entropy is presented for analysis of scanned foot images. An evolutionary algorithm is also employed to find the optimum parameters of GLSC and transform function of the membership values. Resulting binary images as the thresholded images are undergone anthropometric measurements taking in to account the scale factor of pixel size to metric scale. The proposed method is finally applied to plantar images obtained through scanning feet of randomly selected subjects by a foot scanner system as our experimental setup described in the paper. Running computation time and the effects of GLSC parameters are investigated in the simulation results.

Key words: *Anthropometric measurements, bi-level image thresholding, digital plantar image, evolutionary algorithm, foot scanner device, gray level spatial correlation histogram*

INRODUCTION

Modern plantar pressure measurement technology offers a clinician a potential means of investigating changes to foot function over time or the effects of therapeutic intervention.[1] The use of plantar pressure measurement is developing as the application of this technology evolves from the research laboratory into clinical practice.[2] Developing computer-based measurement systems in clinical practices such as anthropometric diagnosis and treatments has been replaced manual measurements with software-based techniques, which leads to more accurate, repeatable, and easy-to-handle resulting data. A digital foot scanner yields a digital image of the plantar with relatively distributed pressure. Anthropometric measurements can be performed on these images by image processing techniques that in this case, the accuracy of the measurements is determined by the proficiency of the used technique.

Image segmentation is an important and fundamental task in image processing. An important technique for image segmentation is thresholding. Thresholding tries to identify and extract a target (foreground) from its background regarding the distribution of gray levels or texture in image objects. Most thresholding techniques are based on either the statistics of the one-dimensional (1D) histogram of gray levels or on the two-dimensional (2D) co-occurrence matrix of an image. Numerous investigations on 1D-thresholding utilize parametric or non-parametric approaches[3-11] to locate the threshold.[3,6,12] In parametric approaches, the gray level distribution of an object class leads to finding the thresholds. In non-parametric approaches, the thresholds will be obtained in an optimal manner according to some criteria. For instance, Otsu's method chooses the optimal thresholds by maximizing the interclass variance with an exhaustive search.[4] The output of the thresholding operation is a binary image whose one state will indicate the foreground objects, like, printed text, a legend, a target, defective part of a material, etc., while the complementary state will correspond to the background. Depending on the application, the foreground can be represented by lowest gray level and the background by the highest luminance, that is, 0 and 255 in an 8-bit image respectively, or conversely the foreground by white and the background by black. For example, in an image of a document paper, the text as foreground can be assigned with 0, and the background can indicate with 255. Various factors, such as non-stationary and correlated noise, ambient illumination, busyness of gray levels within the object, and its background, inadequate contrast and object size not commensurate with the scene, complicate the thresholding

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operation. Furthermore, the lacks of objective measures to assess the performance of various thresholding algorithms, and the difficulty of extensive testing in a task-oriented environment have been other major handicaps.

Although, the 2D histogram of an image provides useful information, two different with identical histograms can yet have different n^{th} order entropies due to their spatial structure.[13] Therefore, a just histogram shape-based method is not a proper and efficient technique for automated image thresholding, solely. In contrast, co-occurrence thresholding methods have been suggested for threshold selection. They considered the co-occurrence probability of the gray values over its neighbors.

In the clustering-based thresholding methods, the gray level data undergoes a clustering analysis, with the pre-define number of clusters two. Since the two clusters correspond to the two lobes of a histogram (assumed distinct), some researchers investigated on the midpoint of the peaks.[14-17] In studies,[18-20] based on bimodal histogram shape, mixture of Gaussians template were used based on mean-square clustering[21] or employed fuzzy clustering ideas.[22,23]

In this study, we propose an evolutionary parametric image thresholding technique for image analysis of digital plantar images. The spatial neighboring information is formulated as the local similarity index for object-background discrimination. Then, the object is segmented and based upon a calibration system or using only a relativistic system, which only considers the pressure distribution over the plantar area relatively and localized self-comparatively the pressure distribution is graded. The parameters of the algorithm containing thresholds for similarity measure and the size of neighborhoods windows should be set optimally, which are found by an evolutionary algorithm aiming to attain the best segmentation. The criterion for segmentation evaluation is considered as the shape correlation between the segmented object and a reference foot shape object while in the algorithm Shanbag entropy is employed to be maximized aiming to attain the most appropriate threshold.

THE PROPOSED ALGORITHM

Gray Level Spatial Correlation Histogram

In this section, the GLSC histogram defined by[24] is utilized to describe the image local property. Let g (x, y) be the gray value of the pixel located at the point (x, y) in a digital image $G(.) = \{g(x, y) \mid x \in \{1, 2, \ldots Q\}, y \in \{1, 2, \ldots R\}\}$ of size $Q \times R$. For convenience, the set of all gray level is assumed {0, 1,…255} as GL. Then, GLSC histogram is computed as follows. For a pixel located at the point, (x, y), let $N(x, y)$ be the number of the pixels of which the gray value is close to it in the corresponding $N \times N$ neighborhood, where N is a positive odd number. The $N(x, y)$ is calculated as

$$N(x, y) = \sum_{i=\frac{N-1}{2}}^{\frac{N-1}{2}} \sum_{j=\frac{N-1}{2}}^{\frac{N-1}{2}} if(|g(x+i, y+j)| \leq \zeta \tag{1}$$

Where

$$if(|g(x+i, y+j) - f(x,y)| \leq \zeta) = \begin{cases} 1 & if\ |g(x+i, y+j) - f(x,y)| \leq \zeta \\ 0 & if\ |g(x+i, y+j) - f(x,y)| \leq \zeta \end{cases} \tag{2}$$

While computing the $N(x, y)$, disregarding the N rows from the top and bottom and N columns from the sides. The pixels gray value, $g(x, y)$, and $N(x, y)$ are used to construct the GLSC histogram using

$$h(k, m) = \text{prob}\ (g(x, y) = k \text{ and } N(x, y) = m) \tag{3}$$

Where $k \in GL$ and $m \in \{1, 2, \ldots N \times N\}$. The normalized histogram is approximated by using the following formula

$$\hat{h}(k, m) = \frac{\text{number of pixels with gray value } k \text{ and } m \text{ pixels of similar gray value in } N \times N \text{ neighborhood}}{\text{number of pixels in the image}} \tag{4}$$

Figure 1 shows a digital plantar image, its 2D gray scale histogram and GLSC histogram corresponding to $N = 5$ and $\zeta = 4$. The object and the background are usually the major parts in image and their gray values are relatively homogeneous compared with noise and edge. The regions with high m value in GLSC histogram correspond to object or background more probably while the regions with low m value correspond to noise or edge oppositely.

ENTROPIC CRITERION FUNCTION

Shanbag[25] considers the fuzzy memberships as an indication of how strongly a gray value belongs to the background or to the foreground. In fact, the farther away a gray value is from a presumed threshold (the deeper in its region), the greater its potential belonging to a specific class. Thus, for any foreground and background pixel, which is i levels below or i levels above a given threshold T, the membership values are determined by

$$\mu_f(T-i) = 0.5 + \frac{P(T) + \cdots + P(T-1-i) + P(T-i)}{2P(T)} \tag{5}$$

That is, the measurement of belonging to the foreground, and by

$$\mu_b(T+i) = 0.5 + \frac{P(T+1) + \cdots + P(T-1+i) + P(T+i)}{2(1-P(T))} 0.5 \tag{6}$$

respectively. On the gray value corresponding to the threshold, one should have the maximum uncertainty, such that $\mu_b(T) = \mu_f(T) = 0.05$, obviously and hence, the threshold, T, is found as it minimize the sum of the fuzzy entropies

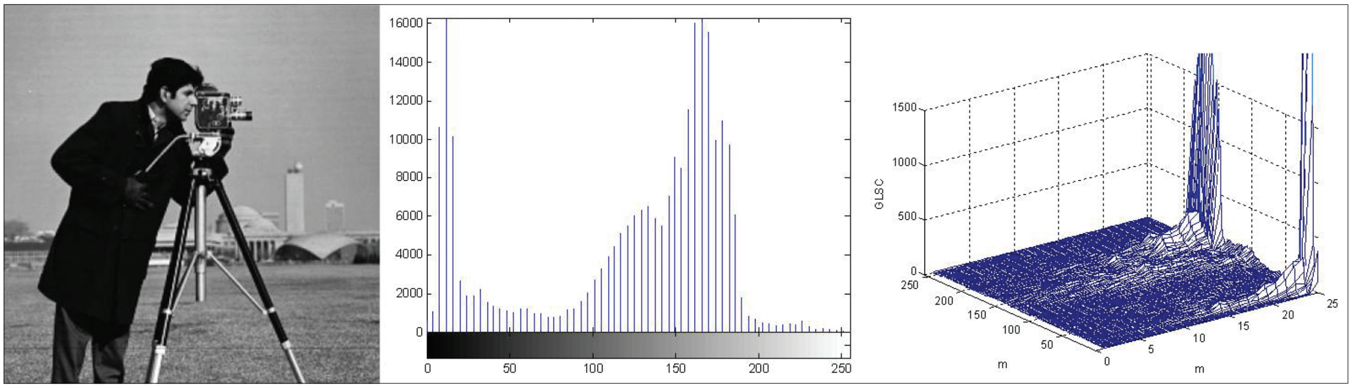

Figure 1: A digital plantar scanned image, its two-dimensional histogram and its gray level spatial correlation histogram (left to right)

$$T_{\text{opt}} - \arg\min_T \{| II_0(T) - II_1(T) |\} \tag{7}$$

$$H_0(T) = -\sum_{g=0}^{T} \frac{p(g)}{P(T)} \log[\mu_0(g)] \tag{8}$$

$$H_1(T) = -\sum_{g=T+1}^{c} \frac{p(g)}{1-P(T)} \log[\mu_1(g)] \tag{9}$$

Since, one wants to get equal information for both the foreground and background. The method of[26] relies on the maximization of fuzzy event entropies, namely, the foreground A_f and background A_b sub-events. The membership function is assigned using Zadeh's *S*-function in.[27] The probability of the foreground sub-event Q (A_f) is found by summing those gray value probabilities that map into the A_f sub-event:

$$Q(A_f) = \sum_{\mu(g)\in A_f} p(g) \tag{10}$$

And similarly for the background,

$$Q(A_f) = \sum_{\mu(g)\in A_f} \rho(g) \tag{11}$$

As

$$H(A,\mu_A) = -\frac{1}{\log^2}\left[Q(A_f)\log Q(A_f) + Q(A_b)\log Q(A_b)\right] \tag{12}$$

In other words, $Q(A_i)$, $i = f, b$, corresponds to the probabilities summed in the g domain for all gray A_i sub-event. One maximizes this entropy of the fuzzy event over the parameters (*a, b, c*) of the *S* function. The threshold *T* is the value *g* satisfying the partition for $\mu_A(g) = 0.5$.

The Proposed Algorithm

The proposed thresholding method is based on a spatial correlation histogram, which formulates the localized similarity measures and Shanbag Entropy, which serves as an objective function to be maximized by an evolutionary algorithm. We employ simple genetic algorithm as the optimization tool to find the optimum parameter set. First of all, the probabilities of the object and background is computed, which is given by

$$p(k,m) = \hat{h}(k,m) \tag{13}$$

Where $k \in GL$ and $m \in (1, 2, \ldots N \times N)$

Thresholding an image at a threshold *thr* is equivalent to partitioning the set G in to two disjoint subsets: $G_A = \{0, 1\ldots thr\}$ and $G_B = \{thr + 1, thr + 2, \ldots 255\}$. Let G_A denote object and GB denote background in this paper. The probability distribution associated with object and background are given by

$$\left(\frac{p(0,1)}{P_A(T)}, \ldots, \frac{p(0,N\times N)}{P_A(T)}, \frac{p(1,1)}{P_A(T)}, \ldots, \frac{p(T,N\times N)}{P_A(T)}\right) \tag{14}$$

And

$$\left(\frac{p(thr,1)}{P_A(T)}, \ldots, \frac{p(0,N\times N)}{P_A(T)}, \frac{p(1,1)}{P_A(T)}, \ldots, \frac{p(T,N\times N)}{P_A(T)}\right) \tag{15}$$

Where

$$P_A(T) = \sum_{k=0}^{thr}\sum_{m=1}^{N\times N} p(k,m), P_B(T) = \sum_{k=thr+1}^{255}\sum_{m=1}^{N\times N} p(k,m)$$
$$\text{and } P_A(T) + P_B(T) = 1.$$

In the proposed hybrid algorithm, the bi-level thresholding is used to classify pixels to dark group (supposedly object) or bright group (supposedly background). With this aim, two fuzzy sets, dark and bright may be considered, whose membership functions are defined as below (π function).

$$\mu_{dark}(t)\begin{cases} 1 & t \le a \\ 1-\dfrac{2}{(c-a)^2}(t-a)^2 & a < t \le \dfrac{a+c}{2} \\ \dfrac{2}{(c-a)^2}(t-c)^2 & \dfrac{a+c}{2} < t \le c \\ 1 & t > a \end{cases} \tag{16}$$

$$\mu_{bright}(t)\begin{cases} 0 & t \le a \\ \dfrac{2}{(c-a)^2}(t-a)^2 & a < t \le \dfrac{a+c}{2} \\ 1-\dfrac{2}{(c-a)^2}(t-c)^2 & \dfrac{a+c}{2} < t \le c \\ 1 & t > c \end{cases} \tag{17}$$

Here, t is the independent variable, a and c are parameters determining the shape of the above two membership functions, which is known as π function. It should be mentioned that for every t the sum of the membership values to the dark and to the bright sets equals one. In the proposed algorithm, the genetic algorithm is used to obtain the values for a and c. The details of the proposed algorithm are described below.

Evolutionary parametric GLSC-based algorithm

Step 1: Input the plantar image
Step 2: Compute the normalized Gray level Spatial Correlation histogram $\hat{h}(k,m)$
Step 3: Compute the probabilities of the gray levels' occurrences
Step 4: Initialize the similarity threshold and neighborhood window size GLSC histogram as $N < 0.05 \times$ Image width and $1 < \zeta < 0.1 \times (G_{max} - G_{min})$ where G_{max} and G_{min} are highest and lowest gray levels of image pixels
Step 5: Use Shanbag entropy as the objective function and the GLSC histogram of the image as the feature space. Calculated membership values are independent variables. Membership Functions' shapes' parameters and GLSC histograms' parameters are sub-variables varying in their search space
Step 6: Initialize genetic algorithm with defined structure and user-defined cycle and operation parameters
Step 7: Run GA and obtain optimum values of independent variables subject to maximize the objective function
Step 8: Perform the image segmentation
Step 9: Check the shape correlation between segmented foot shape and the reference shape
Step 10: If lower than a threshold repeat the steps above with different user-defined parameters, otherwise go to the next step
Step 11: Grade the color intensity difference in the segmented object and proportionate them to pressure distribution according to the calibration values
Step 12: Print the output graphically and numerically

PLANTAR SCANNING

Human foot with its complex structure plays an important role in the human locomotion. Feet play as external surface in stance and gait phase. The structural foot descriptions along with its geometrical anthropometric variables are important variables. There are 26 anthropometric measures, which fully describe the morphological characteristics of feet. Foot anthropometry plays a vital role in medical rehabilitation, sport science, and footwear design etc. In this paper, we placed an experimental setup in the lab. The setup contains an A3 scanner, a laptop and implemented software, which is available on demand. Then, a box with a white glass on top are designed to place on the scanner. Subjects were asked to stand still on the scanner [Figure 2] and the software start to scan the feet and the images are saved for later analysis.

Figure 3 shows an example of plantar scanned image obtained from our setup. The original images are often vague, abnormal (these cases are subject to redo the scan), and noisy.

EXPERIMENTAL RESULTS

The first part of the simulation is on assessment of the proposed thresholding method by studying the impact of its structural parameters. It means the effect of ζ and N on the segmentation correlation value is studied first. In the next part, the time characteristics of the proposed algorithm as complete running computation time, optimization running time and computation time in MATLAB 7.6.0 (2008) and C++ (V.S. 6.0) implementing in the same hardware system are investigated. All simulations are performed in an Intel Core 2 Due CPU @ 2.20 GHz with a 2.87 GB RAM personal Laptop.

As it can be seen from the Table 1, windows size and the similarity threshold parameter ζ affect the segmentation correlation factor which is a non-scale template matching quantity. Windows sizes 3×3 and 5×5 and four different values of ζ are intentionally chosen to show the segmentation correlation for different optimization parameters values. For our problem, population size of 50 and totally 500 generations are optimum user-defined parameters, even though with larger generations and population size higher segmentation correlation value is achieved. The reason for this selection is the computation time, which goes higher than 30 s for larger user-defined parameters. For the selected population size and generations the optimum

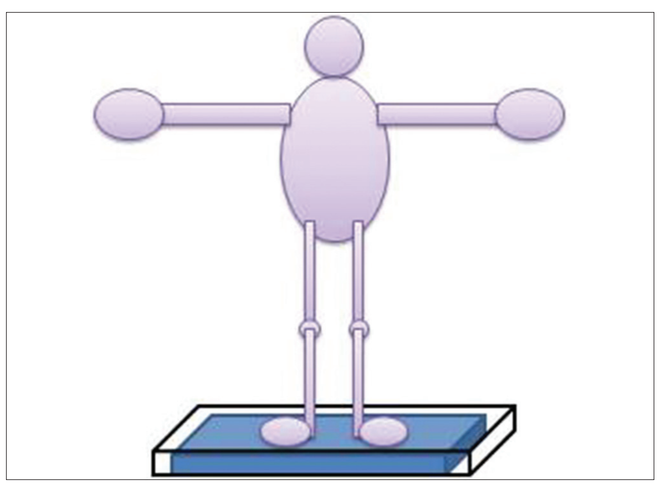

Figure 2: The diagram of experimental setup used for foot scanning

windows size of neighborhood for GLSC histogram is 5×5 and the optimum value for $\zeta = 7$ is found according to our implementations. For smaller windows size as 3×3 the optimum ζ value is found differently since the similarity is measured inside windows and the threshold for similarity is related to the windows size. However, the user sets the optimization parameters as large as the satisfactory results obtained while considering the computation time and the global convergence. Figure 4 shows examples of digital plantar images and the corresponding segmented images obtained by the proposed algorithm.

As the proposed algorithm is to be used in the software of the developing instrument, the computation time is somewhat important for the user. However, the process is not performed in real time and it does not necessarily require real time image processing. The foot is located on the scanner statically and the scanning process goes on. After the data acquisition is performed, the data undergoes processing and analysis, which comprise image storing, image profiling, loading and image enhancement, noise filtering (optional), segmentation, and anthropometric measurements. It means the image processing in plantar scanner systems is carried out offline but it should take time reasonably. Therefore, we try to limit the computation time of the complete running time of the proposed algorithm to 10 s. Table 2 gives the computation time of the proposed algorithm and the optimization process solely (almost all computation time and complexity of the proposed algorithm correspond to the optimization process) written

Figure 3: Samples of plantar images scanned through the experimental setup of foot scanner

Table 1: Segmentation correlation averaged over 10 runs of genetic algorithm with different user-defined parameters and different neighborhood windows size and ζ

	Windows=3×3				Windows=5×5			
	ζ=1	ζ=3	ζ=7	ζ=15	ζ=1	ζ=3	ζ=7	ζ=15
Pop: 20, Gen: 100, Natural GA operators	0.32	0.37	0.34	0.24	0.33	0.47	0.61	0.32
Pop: 20, Gen: 200, Natural GA operators	0.32	0.39	0.35	0.24	0.34	0.47	0.64	0.32
Pop: 50, Gen: 100, Natural GA operators	0.34	0.42	0.37	0.29	0.37	0.55	0.76	0.51
Pop: 50, Gen: 500, Natural GA operators	0.41	0.48	0.42	0.34	0.51	0.64	0.84	0.61
Pop: 100, Gen: 1000, Natural GA operators	0.43	0.52	0.45	0.39	0.52	0.66	0.84	0.62

GA – Genetic algorithm

Table 2: Computation time of the proposed algorithm with different optimization parameters in MATLAB and C++ programming language (rounded running time in second)

GA parameters	MATLAB 7.6.0 (2008)		C++ (Visual Studio 6.0)	
	Optimization	Complete run	Optimization	Complete run
Population: 20 and generations: 50	1.1 s	1.2 s	0.2	0.2
Population: 20 and generations: 100	2.1 s	2.2 s	0.3	0.3
Population: 50 and generations: 100	4.8 s	4.9 s	0.9	0.9
Population: 50 and generations: 500	9.4 s	9.5 s	4.1	4.2
Population: 100 and generations: 1000	34.5 s	34.6 s	11.2	11.3

GA – Genetic algorithm

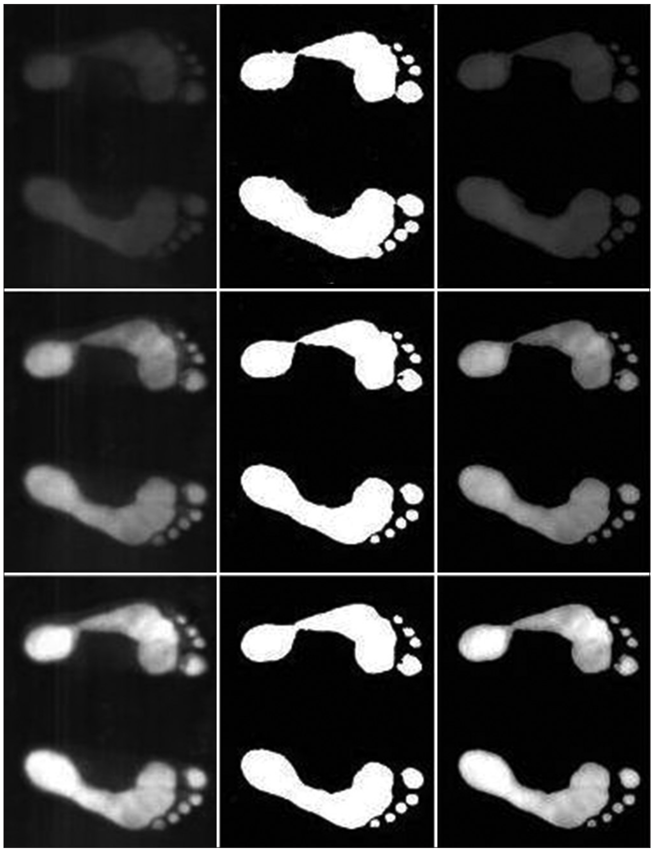

Figure 4: Samples of digital plantar pressure distribution images, scanned images (left), binary images (amid) and segmented plantar area

in MATLAB m-file and C++ programming language. The base and fundamentals of MATLAB are Fortran and C codes but "for-end" loops are the main complexities. Programming in C++ language is more beneficial than programming in MATLAB in term of running time. For five GA parameter sets, running time of the proposed algorithm and the optimization process solely are given in Table 1 for two implementation environment and the units are in second. As it is apparently seen, with higher population size and generations the global optimum is found more accurate in longer time. Considering our defined time limit for image processing in 10 s, it can be inferred that the population size and generations should be set to pop_size: 50 and gen_size: 500 respectively if the program is written in MATLAB. Hence, the segmentation correlation value is found according to Table 1.

CONCLUSION

In this paper, we proposed a hybrid algorithm for digital scanned plantar image thresholding based on Shanbag entropy and the gray level spatial correlation histogram. An evolutionary algorithm is employed to characterize the parameters of GLSC histogram and the membership values for gray levels. The proposed algorithm was described in details and in summary in the paper. It was also evaluated in two schemes. First the effects of GLSC parameters were investigated and then the computational time of the proposed algorithm was studied. Time analysis and parameter dependency of the method were performed. the proposed automation system consisting of the experimental set up and the algorithmic software makes anthropometrist able to do accurate anthropometric measurements on his/her subjects' plantar pressure distribution.

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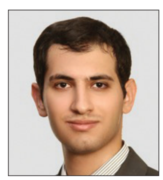

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