Automatic Femur Depth Estimation in Children Under 5 Years Old Using Ultrasound Imaging

R. Erquínigo[1], A. Roman-Gonzalez[2] and M. Zimic[2]

***Abstract*— The automatic estimation of geometric musculoskeletal parameters has been developed in several studies with validated techniques such as Magnetic Resonance and Computed Tomography. The use of ultrasound arises as a technique free of ionizing radiation that allows to observe the internal structures of the musculoskeletal tissues, which however has as a disadvantage the lack of a defined protocol of acquisition that depends to a great extent on the operator. The inherent noise in the acquisition of ultrasound images makes interpretation difficult, so trained personnel are needed to distinguish the structures of interest. This article proposes a method that uses modern techniques of ultrasound image preprocessing in order to segment the bone-muscle border in axial ultrasound images of the distal femoral metaphysis. The aim is to automatically estimate the thickness of the soft tissue upper the distal femoral metaphysis in children younger than 5 years. This parameter can be used in the formulation of a model that estimates weight and height in children under 5 years. We used 457 ultrasound images corresponding to 24 boys and 19 girls. The results show that the selection logic of the region of interest should be improved when comparing the automatic and manual estimates.**

***Keywords*— *ultrasound, echography, image processing, bone, segmentation*.**

I. Introduction

To the new methods for processing low-cost probes ultrasound images to automatically diagnose pneumonia in children under 5 years old (Barrientos [6]), methods can be added for estimating weight and height in bedside children, in order to determine the dose of medication that the patient needs. For this purpose, the thickness of the soft tissue (muscle, fat and skin) upper the frontal side of the distal femoral metaphysis is used as a reference. The distal femoral metaphysis is a flared portion of the femur located in the lower side of it in the upper side of the knee articulation. The metaphysis is the region of long bones between the shaft or diaphysis and the epiphysis (the end of the bone). In this paper we propose an automatic method to estimate the thickness of the frontal side soft tissue upper the distal femoral metaphysis or bone depth using axial ultrasound images of the femur.

This work was supported by the National Fund of Scientific and Technological Development (FONDECYT) and by the Bill and Melinda Gates Foundation

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The purpose of developing an automatic method is that a staff with basic training can use an inexpensive ultrasound probe to estimate the soft tissue thickness in areas of limited resources, avoiding the need for a specialist and the error by interoperation. In a similar way as Amoah et al. [5] who proposed a method for the estimation of gestational age of fetuses from the automatic measurement of fetal femur length, this work was based on modern techniques for bone segmentation in ultrasound images. The greatest number of techniques proposed have been developed in order to use ultrasound for bone segmentation in computer assisted orthopedic surgeries (CAOS). A common used method for the preprocessing of the images is the phase symmetry proposed by Hacihaliloglu [1]. Phase symmetry enables the hyperechogenic surfaces in the ultrasound images to be highlighted in the form of peaks. [1]

The automatic segmentation of bone boundaries based on phase symmetry has been seen in various works such as in Ozdemir [2] (in vivo) and Karlita [3] (ex vivo). In our case we wish to apply a method also based on Phase Symmetry (PS) for the segmentation of the distal femoral metaphysis in the axial plane, with the aim of detecting bone depth. A typical ultrasound image of the distal femoral metaphysis in the axial plane, as shown in figure 1, contains information about the spatial location of the femur. The target structure in this case is the muscle-bone border. It can be distinguished because of both a brighter response than those of the surrounding areas [3] and the presence of an ultrasound artifact called acoustic shadow. The acoustic shadow is a region in the image that appears beneath a region with high acoustical impedance, such as the bone surface, where almost all the ultrasound energy is reflected. As there is almost no penetration of ultrasound energy, the acoustic shadow appears dark. [2] The bone depth can be estimated by the vertical position of the top point from the muscle-bone border as it is related to the real soft tissue thickness above the distal femoral metaphysis. [7]

II. Materials and Methods

A. Database

The database consists of 457 ultrasound B mode images of axial sections of the distal femoral metaphysis with a total of 43 study subjects between 0 and 5 years of age (24 boys and 19 girls). The images were obtained with the Sonosite® MicroMax ™ ultrasound equipment and the HFL38 / 13-6 MHz probe.

B. Database Manual Measurement

The ImageJ software was used to make a manual estimation of the soft tissue thickness or bone depth over the database. These relative measurements were

compared with the automatic estimation of the algorithm (Fig. 1)

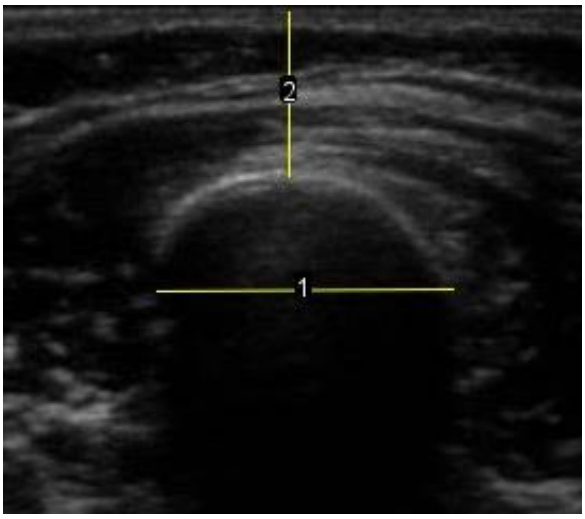

Figure 1: Use of the ImageJ software for manual estimation of the femur bone depth (2)

C. Preprocessing (phase symmetry)

The phase symmetry "PS (x,y)" (1) quantifies the level of summits or peaks of intensity in the image. It is based on the combination of a set of log-Gabor filters used in the frequency domain and set for 2 different scales ("r") and 6 different orientations ("m"). The value of "Tr" represents a noise threshold (2). "erm(x,y)" and "orm(x,y)" are the real and the imaginary part respectively of the two-dimensional log-Gabor filter spatial response (3)(4)

$$PS(x,y) = \frac{\sum_r \sum_m [[|e_{rm}(x,y)| - |o_{rm}(x,y)|] - T_r]}{\sum_r \sum_m \left[\sqrt{e_{rm}^2(x,y) + o_{rm}^2(x,y) + \epsilon}\right]} \quad (1)$$

The log-Gabor filter is defined in frequency as indicated in (4), where "ω" is the frequency in the radial direction, "K" is the bandwidth in the radial direction, "ω_0" is the center frequency, "φ_0" is the orientation of the filter and "σ_φ" is the separation between the orientations of the different filters.

$$e_{rm}(x,y) = \Re\left(F^{-1}\left(2DLGF\left(I(x,y)\right)\right)\right) \quad (2)$$

$$o_{rm}(x,y) = \Im\left(F^{-1}\left(2DLGF\left(I(x,y)\right)\right)\right) \quad (3)$$

$$2DLG(\omega,\varphi) = \exp\left(-\left(\frac{\left(\log\left(\omega/\omega_0\right)\right)^2}{2*\left(\log\left(K/\omega_0\right)\right)^2} + \frac{\varphi-\varphi_0}{2*\sigma_\varphi}\right)\right) \quad (4)$$

For this implementation, the filter parameters were heuristically defined as follows: 2 scales ($1 / \omega_0 = 50$, 80 pixels), 6 directions ($\varphi_0 = 0$ °, 60 °, 120 °, 180 °, 240 °, 300 °), $\sigma_\varphi = 30$ °, $K / \omega_0 = 0.3$, "Tr" and "ε" = 0. Hacihaliloglu proposed a framework for the automatic selection of the log-Gabor filter parameters in [4]. Once the phase symmetry on "I(x,y)" is applied for an image of "M" rows and "N" columns, "PS(x,y)" is obtained.

D. Maximal and downwards concave points determination.

A feature of phase symmetry is to highlight hyperechogenic regions in the form of peaks. It follows that the points belonging to the muscle-bone border are downwards concave relative to the column of the point or pixel. If the border appears as a continuous region without cuts, the points belonging to the frontier will be downwards concave except at the borders of the border, where valleys (upwards concavity) will be formed to distinguish it from other structures. A new binary image "R(x,y)" is obtained after this process.

E. Segmentation

Binarization: A binarization value of 45 (in the 0-255 grayscale range) was obtained heuristically and then applied to "PS(x,y)". The goal is to separate the muscle-bone border from other hyperechogenic structures such as the borders between tissues above and lateral to the bone, but preferring to maintain the integrity of the muscle-bone border (without cuts). In this sense, it becomes likely that the border or region of interest (ROI) will mix with other structures nearby. "B1(x,y)" is obtained after the binarization.

Tagging 1: The image "B1(x,y)" is labeled and the labeled region that meets the following characteristics is selected as the first approximation to the border region:

- Maximum width greater than 60 pixels
- Maximum height greater than 10 pixels.
- Vertical position of all the pixels of the labeled region between 1 and 7*M/ 8.
- Horizontal position of at least one pixel of the labeled region equal to N/2.
- If more than one labeled region meets the above conditions, the one with the highest vertical position (at a greater depth) is selected. Finally, we obtain the binary image "B1sel(x,y)".

Tagging 2: The image "R(x,y)" is zeroed for those values that are zero in "B1sel(x,y)". "B2 (x,y)" is obtained. We label "B2(x,y)" as we did with the first labeling and we get "B2sel(x,y)".

To find the final ROI maximum points: "B2sel(x,y)" becomes the mask such that it presents the downwards concave points (including the maximums) for each ROI column. This mask becomes a more accurate selection of the muscle-bone border. Unlikely "B1sel(x,y)", this mask image separates the border from the surrounding structures that remained together after the binarization. We find the maximum points of "PS(x,y)" and consider only those positions where "B2sel(x,y)" is different from zero. For each column a single maximum point is obtained. If there were more than one, the one that is at greater depth is selected as it is more likely to belong to the border because of the absence of acoustical response beneath the bone border (acoustic shadow). The mask "PM (x,y)" is obtained with the maximum points.

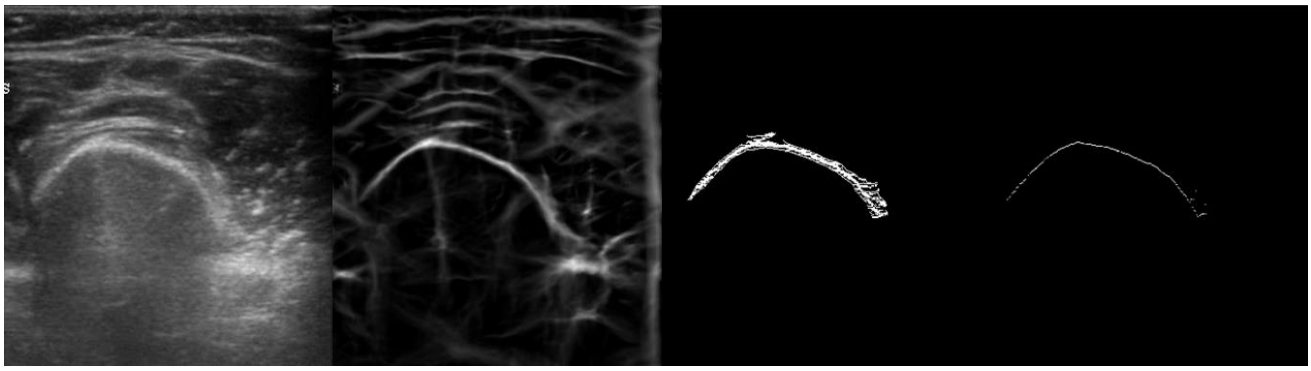

Figure 2: From left to right: Original Image "US(x,y)". Phase Simmetry Image "PS(x,y)". Final selection of the ROI or Muscle-Bone Border "B2sel(x,y)". Maximal points of "PS(x,y)" inside the ROI "B2sel(x,y)": "PM(x,y)".

F. Calculus of the soft tissue thickness or bone depth.

From "PM(x,y)", the point with the lowest depth (upper end of the border) is obtained. The vertical position is multiplied by the constant "C" = 0.01099, which gives an equivalent value in cm.

G. Calculus of the error

To evaluate the performance of the presented algorithm, we define the error metric as shown in (5). Here, "man" and "auth" refers to both the manual and automatic estimates in cm.

$$error(\%) = \frac{|man - auth|}{man} * 100 \qquad (5)$$

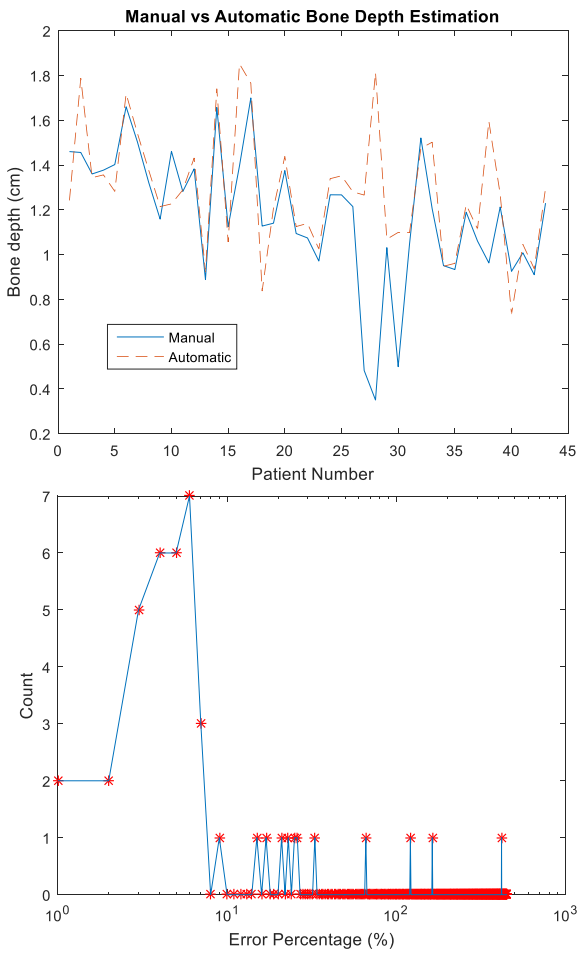

Figure 3: Up: Comparison between the manual and automatic bone depth estimations for the 43 patients. Down: Discrete distribution of error percentage

III. Results, Analysis y Discussion

Figure 3 shows the results of manually and automatically estimating the bone depth. The manual and automatic estimates in cm and the error are presented. It is observed that in 11 of the 43 patients there has been an error of estimation greater than 10%. This error stems from poor selection of the regions of interest "B1sel(x,y)" in first place and "B2sel(x,y)" in second place. The selection of the region of interest follows a simple logic that works well in most cases (32 cases).

To get better results, the selection logic could be improved for obtaining the region "B1sel(x,y)" (more than one per image if necessary for different possible positions of the muscle-bone border in the image). From each "B1sel(x,y)", one or more "B2sel(x,y)" could be obtained. Object descriptors could be defined for the "B2sel(x,y)" region and used for the training of a neural network. The "B2sel(x,y)" region from a set that fits the best would be the final selected "B2sel(x,y)".

IV. Conclusions

A method has been proposed for the segmentation of the Region of Interest corresponding to the muscle-bone border with the aim of automatically estimating the depth of the femur at the frontal side of the distal metaphysis location. The results indicate that the ROI selection logic can be improved.

The final objective is to estimate the size and weight of children under 5 years old through measurements of femur depth and diameter. In a future work, a method will be developed for the automatic estimation of the diameter of the femur that will also be validated against the relative manual estimates.

The presented method is also valid for people older than 5 years old as the distal femoral metaphysis physical characteristics remain similar in spite of the increasing in size as aging.

V. Acknowledgements

The authors are thankful to the National Council of Science and Technology (CONCYTEC), to the National Fund of Scientific and Technological Development (FONDECYT) and to the Bill and Melinda Gates Foundation for the financial aid granted for the development of this work.

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