Program Digest, 2019 IEEE International Ultrasonics Symposium (IUS)
Glasgow, Scotland, October 6-9, 2019

A mobile ultrasound system for majority detection

Holger Hewener
Fraunhofer IBMT
St. Ingbert, Germany
holger.hewener
@ibmt.fraunhofer.de

Christoph Risser
Fraunhofer IBMT
St. Ingbert, Germany
christoph.risser
@ibmt.fraunhofer.de

Lukas Brausch
Fraunhofer IBMT
St. Ingbert, Germany
lukas.brausch
@ibmt.fraunhofer.de

Tilman Rohrer
Saarland University
Medical Center
Homburg, Germany
tilman.rohrer@uks.eu

Steffen Tretbar
Fraunhofer IBMT
St. Ingbert, Germany
steffen.tretbar
@ibmt.fraunhofer.de

Abstract*— Human trafficking for the purpose of sexual exploitation is a problem worldwide and the proportion of underage victims is significant. To identify the minority of a person, the measurement of bone age using X-ray imaging is the gold-standard procedure. Beside several technical and judicial problems like radiation, this technique still requires medical diagnosis and limits the acceptance and practicability. Existing ultrasound systems for bone age determination evaluate changes of speed of sound through bone showing unreliable results for majority determining. In this work a mobile ultrasound system for the purpose of fast and reliable majority determination is developed and clinically evaluated using machine learning for classification without the need of a physician trained for age determination. In women, the complete fusion of the distal growth plate in ulna and radius bones correlates with reaching the age of 18. The existence of this growth plate is measured using the developed mobile multichannel ultrasound system. Its main parts are a low cost and low power FPGA, a fully integrated 8 channel transceiver and a WIFI module for data transfer to a mobile device. A pair of ultrasound array transducers (4 elements with 11x11 mm aperture each, 1 MHz center frequency) is positioned and moved up to 15 mm for reflection and transmission measurements through the forearm resulting in measurements of multiple paths through an existing growth plate leading to more robust results. The detection of growth plate existence was done using machine learning approaches. Different types of artificial neural nets were used. The system has been evaluated successfully in a clinical study with 149 women at Saarland University Medical Center. Classical signal processing analyzing the change of ultrasound signals during transducer movement over the growth plate showed that a difference between underage and legal age women is contained in the data, but classification had to be done using machine learning methods. The best performance for binary majority classification was achieved using a ResNet with an F1 score of approximately 84 % showing the capabilities of the setup. Currently, a multi-center study started to increase the number of data used for training the artificial neural nets, improving these results further while adapting the technology even to male subject groups.

Keywords—bone age, majority detection, growth plate, mobile ultrasound, machine learning

I. INTRODUCTION

The detection of underage victims of human trafficking for the purpose of sexual exploitation is a problem worldwide. Up to now, to identify the minority of a person the measurement of bone age using x-ray imaging is the gold-standard procedure [1]. In women, the complete fusion of the distal growth plate in ulna and radius bones correlates with reaching the age of 18 years (see figure 1). Beside several technical and judicial problems like radiation, this technique still requires medical diagnosis and limits the acceptance and practicability. Existing ultrasound systems for bone age determination evaluate changes of speed of sound through bone showing unreliable results for age assessment to be used for majority determination [2,3].

Fig. 1. Growth plate measurements using X-ray imaging showing ossification states at women with 12, 15 and 18 years of age (from left to right)

A device that is able to substantiate a suspected case of human trafficking of an underage women in an easy and fast way could be used by the officials to install a first screening system (in analogy to breath alcohol analyzers that are being used before further investigations in a suspected case of drunk driving). For such a fast screening system it is not necessary used to assess the absolute age of a person but a robust classifier to detect the presence of a growth plate that correlates closely with the completion of bone growth.

II. STATE OF CONTRIBUTION / METHODS

A. System design

In this work a mobile ultrasound system for fast and reliable majority determination is developed and clinically evaluated using machine learning methods for classification without the need of a physician trained in age determination or medical diagnosis at all. The existence of this growth plate is measured using the developed mobile multichannel ultrasound system with ultrasound array transducers that will be moved alongside the forearm. This leads to a more robust detection of the growth plate compared to existing ultrasound-based bone age measurement systems. In this way the system can be used by authorities at EU borders for example at immigration control at an airport or as mobile control units during police raids.

The overall system consists of an ultrasound electronics for measurements coupled with selected consumer devices via WIFI. This combination reduces the hardware costs of the ultrasound electronics and since the processing to detect the growth plate existence is done on the consumer electronics device it will benefit with new generations of such consumer hardware.

B. Ultrasound electronics

The mobile multichannel ultrasound system provides eight channels for both transmit and receive. Its main parts (see figure 2) are a low cost and low power Xilinx Artix-7 FPGA, a fully integrated 8 channel transceiver Maxim MAX2082 and a low-cost WIFI module for data transfer to a mobile device Espressif ESP-12F.

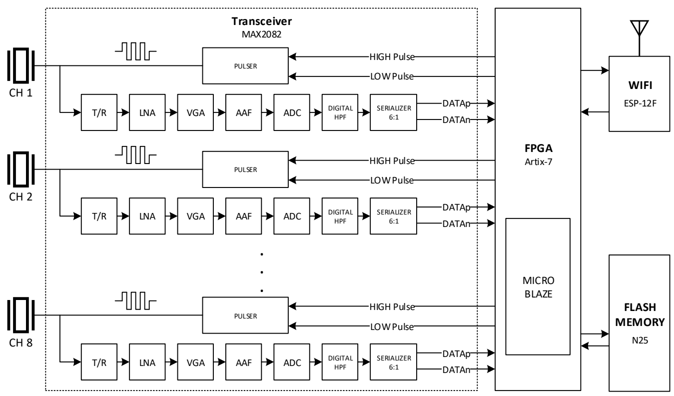

Fig. 2. Simplified block diagram of the electronics design

The system has been specially designed for this mobile use and transducer frequencies ranging from 0.5 to 5 MHz. The FPGA controls all components and handles data management. The focus of the development was to achieve the smallest possible form factor using standard components and to reduce energy consumption to a minimum, while at the same time ensuring a wide range of functions. In the end, a modular design was chosen consisting of two pluggable printed circuit boards with an overall size of 80 x 31 x 16 mm: a power board for supplying the 10 individual voltages needed and a main board with analog front end, digital control and WIFI interface for communication with a mobile device (see figure 3).

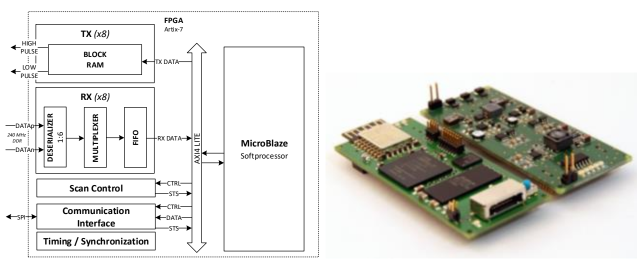

Fig. 3. Firmware components implemented in the ultrasound electronics device FPGA system (left), compact and stackable ultrasound electronics module (right)

The system is ideally suited for use in mobile applications, as it is designed for operation with lithium-ion batteries.

C. Ultrasound transducer array development

A pair of ultrasound array transducers with four elements each is used for transmission and reflection measurements. Each element has an aperture size of 11x11mm and is working at a center frequency of 1 MHz. These are designed to have their focus at a depth of 1.5 cm inside the radius or ulna bone to measure a possible growth plate. The acoustic pressure distribution of such a transducer simulated is shown in figure 4.

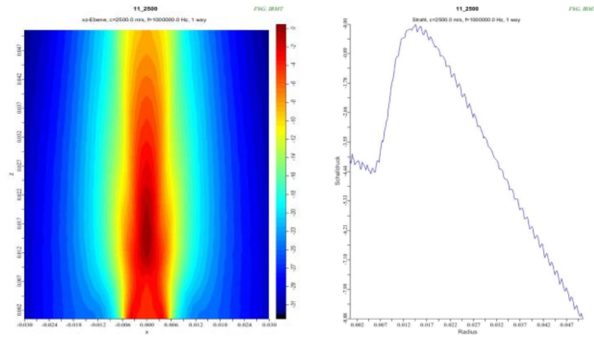

Fig. 4. Simulated acoustic pressure distribution of a single array element regarding a speed of sound of approx. 2500 m/s in bone (left: X/Z-plane, right: acoustic pressure in axial direction)

Every single element of this array can be used individually for measurements by the eight channel ultrasound electronics. The two arrays can be positioned and moved together up to 15 mm in distal and proximal direction with an integrated motor for reflection and transmission measurements through the forearm, resulting multiple path measurements through an existing growth plate. Having multiple ultrasound propagation paths through the forearm and thus through the growth plate should lead to more robust results. The ultrasound transducer is built using a custom composite material (see figure 5).

Fig. 5. Ultrasound array built using composite material during manufacturing without (left) and with (right) dicing of the single acoustic elements

D. System integration

The ultrasound electronics and transducer arrays are integrated with the motor and its controller in a rapid prototype housing with additional EMC shielding on the inside (see figure 6).

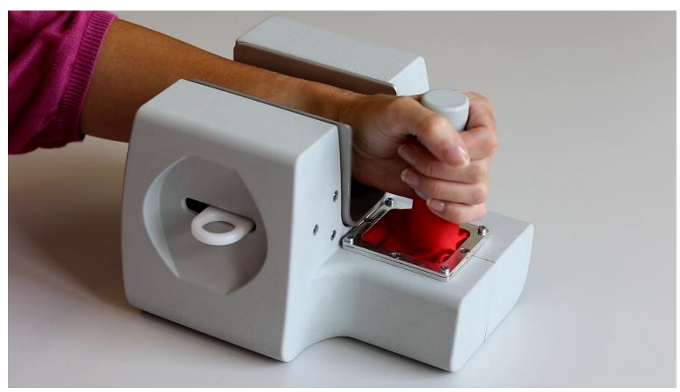

Fig. 6. The measurement system integrated

As the subject to be measured holds on the adjustable handle the transducers are moved with the first skin layer without the need of sliding over the skin. One transducer array is located on the lateral side of the forearm directly on the skin over the radius and ulna bones. The second array on the medial side of the arm is gently pressed against the skin and the underlying soft tissue by a spring mechanism.

All device control and data processing are done on a commercial mobile device using a WIFI connection. Both smartphones and laptops were tested and a tablet style Microsoft Surface laptop was used in the evaluation.

E. *Data acquisition and analysis*

The system features a touchscreen interface on the consumer electronics with a simple workflow including process indicator of the measurements for the clinical use. The workflow consists of eight subsequent measurement blocks (one for each transducer) acquiring reflection and transmission data for each event. The resulting four back and forth motions of the motorized sled with the transducers are performed in less than one minute per patient.

While the transmission signal is always detectable in amplitude and separable in the signal caused by the time needed for the wave to propagate through the bone, the reflection signal received overlaps with the excitation signal caused by the duration of the low frequency excitation. Though, changes in the reflectivity of the bone can still be seen in this signal.

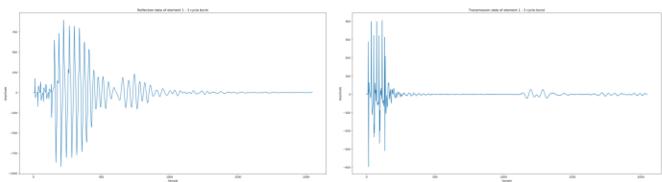

Fig. 7. A-Scan samples illustrating reflection (left) and transmission (right) signal of most distal element(s) acquired with 3 cycles burst

The radio frequency data consists of approx. 250 A-Scans acquired per subject (example see figure 7) containing 2048 samples each. For further analysis, we interpret these A-Scans as one-dimensional vectors containing 2048 elements that can either be processed with classical digital signal processing (DSP) approaches or by exploiting machine learning (ML) methods. The detection of growth plate existence using machine learning approaches implemented different types of artificial neural nets including Fully Convolutional Networks, Multilayer Perceptrons, Residual Networks and a classic k-nearest neighbors algorithm exploiting the dynamic time warping distance.

F. *Clinical study*

After performing tests in compliance to medical standards the system has been evaluated successfully in a clinical study with 149 women at Saarland University Medical Center (see figure 8, left). In the end, data acquired from 135 women was used for the analysis. The prototype system could not be used on 8 subjects caused by their forearms being physically too thin (problem with acoustic coupling) or too thick (problem with motor motion not possible, see figure 8 middle and right). Furthermore, additional 6 subjects were excluded caused by their medical history and current medication giving not reliable information about actual bone growth and bone age with only having an outdated or no X-ray image. None of the subjects found the usage of the system to be uncomfortable with the top layer of skin being pulled slightly (in the range of 15mm) and the ultrasound transducer array on the medial side being pushed towards the forearm during the examination.

For all subjects the diagnosed bone age derived from the X-ray image was used a reference age if available. For all other women the real age was used as ground truth for classification.

Fig. 8. Clinical evaluation of volunteers (left) and patients (middle, right)

III. RESULTS

A. *Evaluation using classical signal processing*

Using classical signal processing to detect the existence of the growth plate was not robust enough in the end. A growth plate without full ossification results in an ultrasound wave that is slower and traveling through more tissue and bone with less ossification. Caused by the lateral extend of the acoustic beam, parts of the wave still travel through normal bone. This results in an overlay of both traveling paths with the signal through the open growth plate submerging in the other signal through bone showing. We detect only small changes in amplitude, frequency content or phase changes caused by wave cancellation (see figure 9).

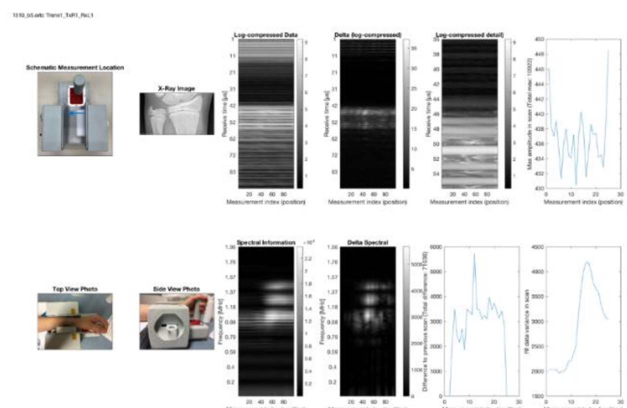

Fig. 9. Analysis of measurement data using classical signal processing looking at the signal during motor motion over the forearm: Amplitude changes (top row) and spectral information (bottom row)

A pure detection of changes in time-of-flight of a detected signal is not possible. The most significant indicator differentiating underage women from full legal age women was seen in the change of ultrasound signals during transducer movement over the growth plate. While older subjects with a growth plate with full ossification show a slight change of ultrasound signal over the transducer movement over the forearm, younger subjects with an open growth plate show a stronger change in the ultrasound wave over the motion caused by diffraction, scattering and reflection of the ultrasound wave on the open growth plate (see figure 10). Although the information about ossification state is contained in the data, the classification cannot be done using hard thresholds.

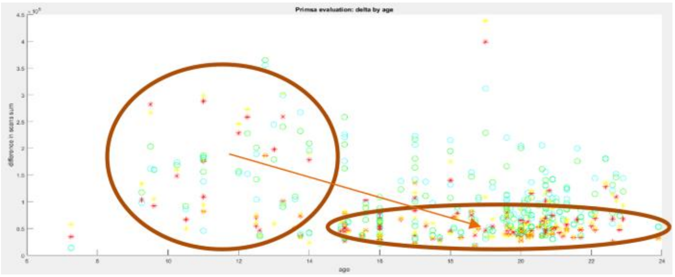

Fig. 10. Plot of absolute value of transmission signal change during motor-based transducer motion (y axis) over subject age (x axis), colored markers per transducer element location, red marker being most distal transducer element

B. Classification using machine learning

The data was analyzed using dimensionality reduction techniques to gain a better understanding of the underlying structure of the information contained. Applying the t-Distributed Stochastic Neighbor Embedding (t-SNE) technique [4] to understand the similarities and differences in the high-dimensional data sets shows that A-Scans do not group according to age groups but cluster for each subject. This underlines the results found with classical signal processing that A-Scans through an open growth plate will not include a unique information but rather must be detected looking at a time series and the change of signal over time/motion. We implemented and evaluated several machine learning methods including time series classification methods including Fully Convolutional Networks, Multilayer Perceptrons, Residual Networks (ResNets) and Radial Basis Function Neural Networks. In addition, we implemented a classic k-nearest neighbors algorithm exploiting the dynamic time warping distance between all collected A-Scans (except the current subject). The collection of multiple A-Scans measured during the motion of the array transducers are collectively classified in a prediction block consisting of a prediction vector containing all single class prediction for each subject. We achieved the best F1 score of approx. 84 % (see table 1) with a ResNet implementation. Figure 11 shows the individual classification results for all subjects.

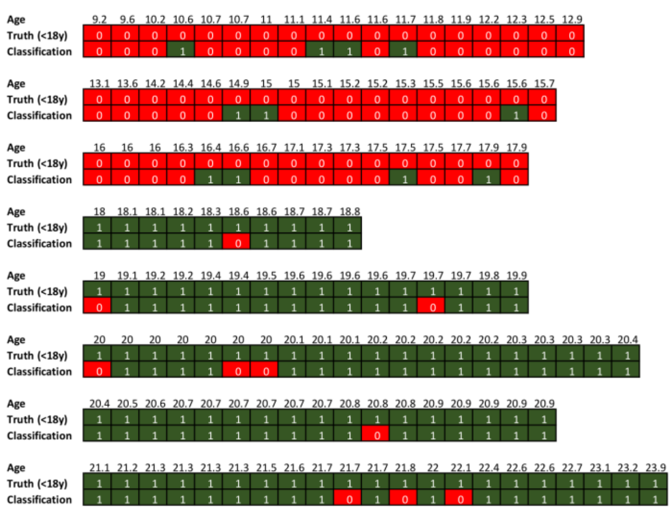

Fig. 11. Classification results using ResNet for all subjects in detail

TABLE I. CLASSIFICATION RESULTS OVERVIEW BY AGE

Proband (bone) age	**Classification result: correct / total (%)**
All	111 / 135 (84,4 %)
<18y	40 / 51 (78,4 %)
>18y	74 / 84 (88 %)
<17y	33 / 42 (78,5 %)
>=17y; <=19y	16 / 19 (84,2 %)
>=19y	65 / 74 (87,8 %)

IV. DISCUSSION / OUTLOOK

While not being able to assess an absolute age of a woman we demonstrated in this work the feasibility of ultrasound-based classification techniques to determine the legal age or majority of a woman. The best performance was achieved with machine learning approaches using a ResNet with an F1 score of about 84 % showing the capabilities of this approach. Applying classical signal analysis showed that a difference between underage and legal age women is contained in the data, but classification cannot be done using hard thresholds. Even though the implementation and evaluation of more sophisticated DSP techniques remains to be done in the future, we expect the ML methods to outperform any DSP method for larger datasets.

Currently, a multi-center study started to increase the number of data used for training the artificial neural nets, improving these results further while adapting the technology even to other subject groups: Male subjects as well as several ethnic backgrounds have significant differences on bone age. This needs to be investigated in this study hinting at a classification using multiple neural networks trained for different gender, ethnic groups and all its permutations. In the end the correlation between bone age and legal age must be further evaluated to determine the reliability of bone age as an indicator for majority detection in general as this proposed procedure relies on the same anatomical feature like the analysis using X-ray imaging.

ACKNOWLEDGMENT

We acknowledge the financial support by the Federal Ministry of Education and Research (BMBF) of Germany in the framework of PRIMSA (grant number 13N13520).

REFERENCES

[1] N. Hassan, F. Noor, S. Ahmad, KM. Fazili, “Age of fusion of the distal radial and ulnar epiphyses from hand radiographs-A study” in Kashmiri population. Sci Justice. 2016;56(6):431-6.

[2] HJ. Mentzel, C. Vilser, M. Eulenstein, T. Schwartz, S. Vogt, J. Bottcher, et al., “Assessment of skeletal age at the wrist in children with a new ultrasound device”, Pediatr Radiol. 2005;35(4):429-33.

[3] A. Castriota-Scanderbeg, MC. Sacco, L. Emberti-Gialloreti, L. Fraracci, “Skeletal age assessment in children and young adults: comparison between a newly developed sonographic method and conventional methods”, Skeletal Radiol. 1998;27(5):271-7.

[4] L. v. d. Maaten and G. Hinton, “Visualizing data using t-sne”, Journal of machine learning research, 9(Nov):2579–2605, 2008.