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Research Article

A Computerized Algorithm of Extracting Acoustic Measures from Prenatal Diagnostic Ultrasound Images

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Abstract

Background: Diagnostic Ultrasound (dUS) images capture acoustic measures. Higher level of acoustic measures may increase the likelihood of adverse neurodevelopment.

Objective: To develop a computerized algorithm to extract acoustic measures from dUS images.

Method: The dUS images of 484 pregnant women in 2014 were extracted from the Electronic Medical Record (EMR) system within an integrated healthcare organization. The retrieved dUS images were processed by the optical character recognition engine, Tesseract, to recognize the embedded texts. A set of matching patterns was constructed to extract the values associated with Thermal Index (TI), Mechanical Index (MI) and transducer frequency from these recognized texts. A sample of 200 randomly selected dUS images was processed by the computerized algorithm and results were compared against the gold standard of perinatal expert reviews.

Results: 54,909 dUS images were extracted from the EMR system. 52,637 of them had at least one of acoustic measures. The mean of extracted TI, MI and transducer frequency were 1.05, 1.08 and 4.34(MHz), respectively. Higher frequencies of dUS (5-7 MHz), higher MI (≥1.00) and higher TI (≥1.00) were used during first trimester, first/second trimesters and second/third trimesters, respectively. The computerized algorithm achieved a performance with sensitivity of 99.0%, 93.3%, 62.0% and positive predictive value of 100.0%, 99.5%, 95.8% for TI, MI and transducer frequency, respectively.

Conclusions: Our study successfully developed a computerized algorithm to extract TI, MI and transducer frequency from dUS images. Implementation of this algorithm can provide values for examining potential effects of acoustic measures on perinatal outcomes and evidence-based decision making.

Introduction

Diagnostic ultrasound (also called sonography) is a diagnostic imaging technique that uses high-frequency sound waves to produce images of structures within internal body [1]. These images can provide valuable information for diagnosing and treating a variety of diseases and conditions. Ultrasound has become an indispensable tool in obstetric practice improving diagnosis of adverse prenatal conditions through providing instant clinical information. It is a standard part of prenatal care in the United States used for assessing fetal viability, biometry, and the position of the placenta, amniotic fluid levels, cervical length and funneling, the safe delivery of the baby as well as many other conditions [2-5]. Its use has increased markedly over a ten-year period, from 1.5 per pregnancy during 1995-1997 to 2.7 per pregnancy during 2005-2006, a relative increase of 80% [6]. The increase was consistent both in high-risk and low-risk pregnancies across all three trimesters with some varied increased magnitudes [7].While it is a widely used diagnostic tool in obstetrics and no adverse health effect from its exposure has been reported, evidence based on animal model have shown that diagnostic levels of ultrasound waves may cause deleterious thermal-mechanical effects on cells and tissues [8-10], leading to disrupted functional connectivity in brain [11,12].

Ultrasound imaging equipment captures various medical image information including, the potential bio-effects related acoustic measures such as Thermal Index (TI), Mechanical Index (MI) and transducer frequency in real-time as the Digital Imaging and Communication in Medicine (DICOM) format [13]. In our care setting, the DICOM structured data only captures a single value of transducer frequency, per image while the ultrasound image inside could contain one to three frequency values. Both TI and MI measures are not available in the DICOM structured data format, instead, they are embedded in the Diagnostic Ultrasound (dUS) images. Therefore, they are not readily available for researchers to investigate its impact on developing fetus. Manual extraction of the acoustic measures from obstetric ultrasound images is a very time consuming, resource intensive process and infeasible if the volume of images is huge. To our knowledge, no computational method has been attempted to obtain the acoustic measures (TI, MI, and transducer frequency) directly from the dUS images. On the other hand, the computerized technique of Optical Character

Recognition (OCR) [14] and Natural Language Processing (NLP) [15-19], have been well developed and extensively used to recognize the characters from images and extract useful information from the unstructured free texts. Therefore, the objective of this study is to develop an effective computerized algorithm to retrieve the acoustic measures generated from obstetric ultrasound scanning during the course of prenatal care to facilitate its use for medical research and incorporate evidence-based medicine in healthcare operations within a large integrated health maintenance organization.

Methods

Care setting and data description

Kaiser Permanent Southern California (KPSC) is an integrated healthcare delivery system composed of 15 hospitals and over 220 satellite medical offices throughout southern California with a comprehensive Electronic Medical Record (EMR) system, and provides services to over 4.5 million active members [20]. The average annual birth delivery in our system is over 36,000 in recent years. Member clinical visit information are captured and stored in the EMR system. For this study, women who had a pregnancy delivered in 2014 were first retrospectively identified from the KPSC prenatal service system, a sample of 500 were randomly selected to be used for the study algorithm development. For each of these 500 pregnant women, the corresponding dUS images captured during radiology department visits (formal dUS images) within the entire pregnancy episode were retrieved from the KPSCEMR system. Currently, the dUS images performed within ob-gyn offices during prenatal visits (informal dUS images) are scanned as documents rather than stored as images. Therefore, the informal dUS images of these 500 subjects are not available for this study. In addition, 18 of these 500 subjects weren't retrieved any formal dUS images. The study was approved by our Institutional Review Board, with waivers of the requirement for informed consent and the Health Insurance Portability and Accountability Act (HIPAA) authorization.

Acoustic measures extraction algorithm

The prenatal dUS image usually contains a number of useful and vital care embedded information including the values of thermal index, mechanical index and transducer frequency, etc. Each dUS image contains only one thermal index value and one mechanical index value, but potential one to three frequency values. To effectively retrieve all of these values, two steps are involved.

Step 1: Recognize text characters from diagnostic ultrasound images: Tesseract [21], an open-source optical character recognition engine available for various operating systems, has been extensively used to recognize the text characters from images. It's considered as one of the most populate open-source OCR engines [22]. Tesseract is free software, released under the Apache License, Version 2.0 [23], and development has been sponsored by Google since 2006. The OCR freeware Tesseract was downloaded from the official site [23] and then installed it in a powerful Linux server with 24 Intel(R) Xeon(R) CPU E5-2630 0 @ 2.30GHz.

A batch process was designed to call the Tesseract OCR engine to process the dUS images sequentially to recognize the text characters embedded in each image and convert them to text strings, and then the retrieved text strings were stored into a corresponding text file for each dUS image frame. Because majority of dUS images has good quality, the OCR engine can recognize the text characters well, and produced reliable text strings for most dUS images. A small percentage of word characters was mess up and converted into non-word characters. For example, "I" of "MI" sometimes was also recognized as the non-word character "|", "l" or the digital "1".

Step 2: Extract acoustic measures from retrieved text string files: The information of MI and TI are usually displayed at the top-right corner of the dUS image, but the transducer frequency could be at either left or right side of dUS image. The matching pattern to extract the values of these measures is pretty straightforward. It begins the abbreviation "MI", "TIb", "TIB" or "Frq", then follow up numerical values with one or multiple spaces between them. Considering the potential variation by the OCR recognition, we summarized and created the following matching pattern Regular Expression (RE) to extract the term-value pairs for MI, TI and transducer frequency.

MI: M(I|i|l|1|\|)\s*(1|0|o)\.\d

TI: T(I|i|l|1|\|)(B|b|S|s)?\s*(1|0|o)\.\d

Transducer frequency: F(R|r)(E|e)?(Q|q)\s*\d(\.\s*\d?| \d)

Where, the symbol \ means escaping next meta character, so \| means matching the symbol |. \s* means zero or multiple space character. \d represents any of 0 to 9 digital number. The symbol | represents 'or' operator. The question mark ? matches zero or one of the previous RE. The parentheses ( ) enclose a group of REs.

The RE beginning part is to match the term MI, TIb or Frq, and the RE ending part is to extract the corresponding value. These regular expressions were implemented through Python language. The step 1 and step 2 were executed at the speed of processing over 3100 dUS images within 1 h by a single processing job in our Linux server.

Computerized algorithm evaluation

A sample of 200 dUS images were randomly selected from the retrieved dUS images for independent adjudication by a perinatal expert. The perinatal expert reviewed each dUS image to abstract the information of MI, TI and transducer frequency, and also documented the specific comments if they were not available. The manual results served as the "gold standard" and compared against the results obtained from the computerized algorithm. The measures of accuracy, including sensitivity, Positive Predictive Value (PPV), were calculated for MI, TI and transducer frequency, respectively. Sensitivity (recall) was defined as the number of dUS images in which MI, TI or transducer frequency was correctly extracted by the computerized algorithm (same as the manual results) divided by the total number of dUS images in which MI, TI or transducer frequency was abstracted by the prenatal expert. PPV (precision) was defined as the number of dUS images in which MI, TI or transducer frequency was correctly extracted as being the same as the manual results by the computerized algorithm divided by the total number of dUS images in which MI, TI or transducer frequency was extracted by the computerized algorithm.

Results

A total of 54,909 formal dUS images were retrieved from the EMR system. The average prenatal visits with formal dUS images

Table 1: The Mean and range of extracted acoustic measures and their percent distributions by trimester at exposure.

Acoustic output measures	Mean (range) of acoustic measures and their percent distribution		
	1st trimester	2nd trimester	3rd trimester
Frequency (MHz)	4.54 (2.80-6.30)	4.46 (2.80-6.00)	4.03 (2.80-6.00)
<3.00	10.53	1.45	11.98
3.00-4.99	68.42	93.17	84.9
5.00-6.99	21.05	5.38	3.13
Mechanical index	1.08 (0.80-1.20)	1.10 (0.50-1.30)	1.01 (0.50-1.20)
< 0.50	0	0	0
0.50-0.99	16.33	15.01	41.88
≥1.00	83.67	84.99	58.12
Thermal index	0.89 (0.30-1.90)	1.08 (0.10-1.90)	0.99 (0.20-1.90)
< 0.50	8.16	1.63	4.27
0.50-0.99	65.31	38.7	51.71
≥1.00	26.53	59.67	44.02

per subject were 1.7, and the average captured dUS image frames per prenatal visit were 65.7. The computerized algorithm successfully retrieved at least one of acoustic measures from 52,637 dUS images, and didn't found any of acoustic measures for the remaining 2,272 dUS images. The overall mean and ranges of the extracted dUS transducer frequency, MI, and TI were 4.34 (MHz) (2.80-6.30), 1.08 (0.50-1.30), and 1.05 (0.10-1.90), respectively. The trimester-specific mean and ranges for the extracted transducer frequency, MI, and TI were presented in Table 1. Higher frequencies of dUS (5-7 MHz) were more likely to be used during the first-trimester. A higher MI (≥1.00) was used in about 84% of the cases during the first- and second-trimesters. On the other hand, a higher TI (≥1.00) was used during the second- and third-trimesters.

Data on the comparison of the computerized results versus the prenatal expert results retrieved from the 200 randomly selected dUS images are shown in Table 2. The computerized algorithm achieved a performance with sensitivity of 99.0%, 93.3%, 62.0% and PPV of 100.0%, 99.5%, 95.8% for retrieving TI, MI and transducer frequency, respectively. With the supplement of structured transducer frequency information, the sensitivity of transducer frequency increased from 62.0% to 90.2% (data no showed).

Table 2: Comparison of performance of the computerized algorithm for thermal index, mechanical index and transducer frequency extraction from diagnostic ultrasound images.

Computerized results	Confirmed by prenatal expert		
	Same	Different	All
TI			
With value	192	0	192
Without value	6	2	8
MI			
With value	181	1	182
Without value	6	12	18
Transducer frequency			
With value	114	5	119
Without value	16	65	81
Performance	TI	MI	Transducer frequency
Sensitivity	99.00%	93.30%	62.00%
PPV	100.00%	99.50%	95.80%

TI: Thermal index; MI: Mechanical index.

The category was defined as "Same" if the computerized results and manual results were identical; otherwise, it was defined as "Different."

Sensitivity = Number of TI, MI or Transducer frequency correctly extracted by the computerized algorithm/number of TI, MI or Transducer frequency retrieved by prenatal expert, respectively.

PPV = Number of TI, MI or Transducer frequency correctly extracted by the computerized algorithm/total of number of TI, MI or Transducer frequency extracted by computerized algorithm, respectively.

Discussion

In this study, we successfully developed a rule-based computerized algorithm and process to extract the acoustic measures from the formal dUS images captured during prenatal visits. Compared to the prenatal expert manual review results of 200 randomly selected dUS images, the computerized algorithm produced a high level of PPV of 100.0%, 99.5%, 94.3% for TI, MI and transducer frequency, and high sensitivity of 99.0%, 93.3%, for TI, MI, but the sensitivity of transducer frequency achieved at only 62.0%. The discrepancy between NLP results and manual results was due to multiple factors. First, the missed retrieving values for TI (2 cases), majority of MI (12 cases) and transducer frequency (65 cases) were due to the OCR engine failure accurate recognition of either the words TI, MI, frequency or their corresponding values. The failure of recognition could be caused by the unreliable quality of dUS images or crowd of text characters in the dUS images. This resulted the OCR engine recognized the text as complete different characters or unable to recognize any characters. For example, the text "MI 1.2" in couple of dUS images was recognized as "m1â.â2", and the text "Frq 2.5" as "ârq 2.5" by the OCR engine. Second, the OCR engine was able to recognize the digitals, but retrieving values different from the original ones in the dUS images, which resulted the false extraction. For example, "MI 0.9" could be misrecognized as "MI 0.5" for false MI extraction, and "Frq 8.0" as "Frq 5.0" for false transducer frequency extractions by the OCR engine. Thirdly, the OCR engine recognized additional non-space characters between the keyword of TI, MI or frequency and the corresponding values. As an example, some cases of "MI 1.2" were recognized as "M|,â1.2". Such cases were unable to pick up by the matching pattern regular expression described in our current study. In our care setting, the information of transducer frequency was presented at either left or right side and near close to the pixels of dUS images. The lower sensitivity of transducer frequency extraction was largely due to the entanglement of transducer frequency text strings with the image pixels, which resulted in OCR engine failure to recognize the corresponding text strings. However, the transducer frequency was recorded into the DICOM format structured data (one value per image frame) and stored into the EMR image system. With the supplement of the structured data, the sensitivity of transducer frequency increased from 62.0% to 90.2% with a significant improvement.

This study sampled from a large and diverse population of pregnant women and health care delivery system, provides support for investigators to reliably extract important ultrasound imaging data that can inform evidence-based practice. There are, however, several potential limitations that need to be acknowledged and overcome. First, our computerized algorithm replied on the Tesseract OCR engine to recognize the text characters embedded in the dUS images. Therefore, the quality of dUS images and Tesseract OCR engine performance determinate the performance of our algorithm as well. Second, there are other additional patterns may be not included in our current matching patterns. For example, the Tesseract OCR engine recognized additional non-space characters between the keywords and their corresponding values. Our future work can explore more dUS images and discover other potential matching patterns from the retrieving text strings by the OCR engine. Finally, our computerized rule-based algorithm was based on the formal dUS images in our care setting. Implementation of this algorithm in the informal dUS images and other care setting may produce some variation of performance. But the results should not be significantly different from our findings.

Despite these limitations, our study developed a computerized algorithm to effectively extract the acoustic measures (TI, MI and transducer frequency) from diagnostic ultrasound images captured during the prenatal visits. Implementation of this algorithm to retrieve the acoustic measures in a systematic and automated way can greatly facilitate the clinical medical research examining the potential effect of ultrasound imaging on developing fetus.

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