A Fuzzy Decision System for Ultrasonic Prenatal Examination Enhancement

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1 Introduction

We report here on the development of a fuzzy decision system to semi-automate ultrasonic prenatal examinations in order to reduce their cost, minimize exposure time of the fetus to ultrasonic radiation, and to provide a uniform examination for all patients. To our knowledge, this is the first successful application of its kind, and paves the way towards development of a computationally intelligent system for prenatal examination.

Obstetric scanning is an established technique for noninvasive examination of the fetus. However, arguments can be made against its routine use. These include the operation's financial cost, concerns for safety of the developing fetus, and the potential to adversely affect the management of the pregnancy due to misuse or misinterpretation of sonographic findings.

Of these, financial cost is probably the most important obstacle to routine scanning. In the United States alone, the cost for one ultrasound examination for each of the 3 million babies born each year would total around $450 million. The potential cost of scanning each pregnancy twice approaches $1 billion per year [1].

The vast majority of "low-risk" obstetric sonograms are performed or supervised by physicians who actually devote a minority of their time to ultrasound and who have relatively little experience in the prenatal diagnosis of congenital malformations. When such examinations are also limited to one or more biometric measurements without a survey of fetal anatomy, many malformations will be missed. Most important in regard to detection of fetal anomalies are standard ultrasound planes and anatomic landmarks that are recommended during the second and third trimesters. Incorporation of these standard views into routine obstetric scanning has the potential to detect or exclude the vast majority of major anomalies [2].

2 Approach

Generation and analysis of prenatal ultrasonic images is a complex operation composed of numerous tasks from different areas in the engineering and biomedical fields. We outline here the major steps identified for generation of a first level semi-automated prenatal ultrasonic examination system based on fuzzy inference:

(1-3) The first three steps involve capturing the raw image, converting it into a desired format, and using various digital signal processing techniques to segment the image. These are important steps but have been simulated under this work so that the function of evaluating and diagnosing the segmented image can be concentrated on. Significant work has been performed in these areas [3, 4, 5]. Applications in biomedicine include development of human brain MRI segmentation schemes [6, 7, 8], and preprocessing of textural features of ultrasonic images [9].

(4) In Step 4 upper and lower bounds are established for typical measurements of the biometric items of interest, from an extensive library of data [1] on normal growth measurements as a function of

menstrual age. While there are many growth measurements that can be investigated, we focus here on the three primary measurements of head circumference H, abdominal circumference A, and femur length F. Each of these bounds is actually a family of bounds based on menstrual age.

(5) Step 5 involves development of a decisional algorithm to group the image segments from Step 3 into one of four groups: head, abdomen, femur, and other. This step uses a series of IF-THEN statements to determine whether the captured and segmented image meets minimum requirements for further processing.

(6) Membership functions for three grades of normality for biometric items of interest are derived next, in Step 6. Data from [2] has been used in the development of the membership functions, as a function of menstrual age.

(7) In Step 7 decisional algorithms are developed to determine the degree to which the items identified in Step 5 are "normal". This uses a series of IF-THEN statements as in Step 5, however, this step generates a fuzzy set, i.e. normal, slightly abnormal, or abnormal.

(8) Finally in Step 8 we report the elements found and the status (fuzzy answer). This is the last step in our process but is the beginning for the physician. If everything is normal there is little remaining analysis. However, if any element comes back abnormal the physician should go back and examine the item.

3 System Development

Steps 4 through 8 are developed in this section. Under this work the three biometric measurements of head circumference, abdominal circumference, and femur length are examined. Simplified geometries for the head-abdomen circumferences and femur are used.

3.1 Bounds on Biometric Measurements

Using histograms of data (from [1]) the following bounds are established for typical measurements of the head circumference H, abdominal circumference A, and femur length F for a fetus with a menstrual age of 20 weeks.

$$13.5 \text{ cm } \leq H \leq 22.5 \text{ cm} \tag{1}$$

$$10.5 \text{ cm } \leq A \leq 19.5 \text{ cm} \tag{2}$$

$$2.2 \text{ cm } \leq F \leq 4.0 \text{ cm} \tag{3}$$

It is clear from comparing Eqs. (1) and (2) that there is a great deal of overlap in values of H and A. The recommended solution to this problem is to use spatial filtering to aid distinguishing between the head and abdomen. This is possible since in normal fetuses the femur is connected to the abdomen, not the head.

Similar bounds can be established for head circumference, abdominal circumference, and femur length for fetuses with menstrual ages from 12 to 40 weeks utilizing existing databases.

3.2 Decisional Algorithm for Element Identification

Inputs to the decisional algorithm for element identification (Step 5), are: estimated fetal age, element circumference if round or elliptical, and length if rectangular, as well as spatial orientation. Figure 1 is an example of a sample input data set. The input data sets for each element of a segmented image are arrays of the following form:

$$\text{Image} = (\text{shape, size, location})$$

where

$$\text{shape} = \begin{cases} 0 & : \quad \text{circular} \\ 1 & : \quad \text{rectangular} \end{cases}$$

size is a floating point number in cm for circumference or length, and

$$\text{location} = \begin{cases} 0 & : \quad \text{top zone} \\ 1 & : \quad \text{middle zone} \\ 2 & : \quad \text{bottom zone} \end{cases}$$

The ability to distinguish between bones of the arm and femur are based on size and relative location. Since the head and abdomen are the only circular body elements, the only problem is to distinguish between them.

The steps in the element identification decisional algorithm are as follows:

(a) Sort elements into two groups based on shape, one for circular, one for rectangular.

(b) Determine if image meets minimum requirements for further processing:

   (i) Must have at least 1 circular element within the bounds established by Eq. (1) in the top zone and Eq. (2) in the middle zone.

   (ii) Must have at least 2 rectangular elements within the bounds established by Eq. (3) in the bottom zone.

   If these conditions are not met, image is abnormal and should be reviewed by physician.

(c) If more than 1 circular element is identified by step (b) above in either the top or middle zone, then image is abnormal and should be examined by a physician.

(d) If more than 2 rectangular elements are identified by step (b) in the bottom zone, then image is abnormal and should be examined by a physician.

(e) Assuming steps (a)–(d) have been completed satisfactorily, the head, abdomen, and femurs have been identified and are ready for further processing.

3.3 Membership Function Development

Membership functions for three grades of normality have been developed for head circumference, abdominal circumference and femur length. These membership functions are based on the same data used to develop the bounds for H, A, and F in Section 3.1, and are shown in Figs. 2–4. There are five different classes of membership functions: *Abnormal Small* (AB), *Slightly Abnormal Small* (SAS), *Normal* (N), *Slightly Abnormal Big* (SAB), and *Abnormal Big* (AB).

Figure 5 shows the membership functions for a Normal fetus (N), Slightly Abnormal fetus (SA), and an Abnormal fetus (AB). The scale of 1 through 10 for fetal status in Fig. 5 is arbitrary and is used only to show degrees of normality. These three membership functions will be used in the following section in the consequents of the IF-THEN rules.

3.4 Decisional Algorithm to Classify Fetus

Fuzzy inference is implemented using a series of rules to classify a fetus as normal, slightly abnormal, or abnormal based on measurements of head circumference, abdominal circumference, and femur length. The implication method chosen (shaping of the consequent) is clipping (min operator). The seven IF-THEN rules implemented for fetal evaluation are:

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R1 = IF H is (AS .OR. AB) .OR.
     IF A is (AS .OR. AB) .OR.
     IF F is (AS .OR. AB) THEN
     Fetus is AB.

R2 = IF H is (AS .OR. AB) .AND.
     IF A is (SAS .OR. SAB) .AND.
     IF F is (SAS .OR. SAB) THEN
     Fetus is AB.

R3 = IF H is (SAS .OR. SAB) .AND.
     IF A is (AS .OR. SAB) .AND.
     IF F is (N .OR. SAB) THEN
     Fetus is AB.

R4 = IF H is (SAS .OR. SAB) .OR.
     IF A is (SAS .OR. SAB) .OR.
     IF F is (SAS .OR. SAB) THEN
     Fetus is SA.

R5 = IF H is (N .OR. SAB) .AND.
     IF A is (SAS .OR N) .AND.
     IF F is (SAS .OR. SAB) THEN
     Fetus is SA.

R6 = IF H is N .AND. A is N
     .AND. F is (SAS .OR. SAB)
     THEN Fetus is SA.

R7 = IF H is N .AND. A is N
     .AND. F is N THEN Fetus
     is N.
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The seven clipped consequent membership functions are aggregated using the max operator. Finally, centroid defuzzification is used to arrive at a single number representing degree of normality. This is in turn classified as either abnormal, slightly abnormal, normal, or ambiguous based on the defuzzified output's relative membership in each of the consequent fuzzy sets.

4 Results and Discussion

Results from an emulation of the fuzzy inference system developed in the previous section are presented here. Table 1 gives a comparison of predicted fetal status versus results from the simulation for a represen-

Case #	H (cm)	A (cm)	F (cm)	Predicted Result	Simulation Result
1	12.0	21.0	3.0	Reject	Reject
2	17.9	15.0	3.1	Normal	Normal
3	14.5	12.0	2.5	Abnormal	Abnormal
4	16.2	13.0	3.5	Slightly Abnormal	Slightly Abnormal
5	19.5	17.5	3.6	Slightly Abnormal	Slightly Abnormal
6	21.0	15.0	3.1	Abnormal	Abnormal
7	18.4	14.5	3.0	Normal	Normal
8	15.0	17.1	3.5	Abnormal	Ambiguous
9	19.5	15.0	3.1	Slightly Abnormal	Slightly Abnormal
10	20.0	16.9	3.6	Slightly Abnormal	Slightly Abnormal

Table 1: Comparison of expected fetal examination results to those from fuzzy inference.

tative sample of biometric measurements.

Table 1 presents the simulation results for a very limited number of cases. Already in this small sample, 90% of the results from the simulation match the predicted results. The only instance when the predicted result did not match the simulation is case 8. The simulation returned ambiguous since rule 1 and 4 both returned a weight of 1 resulting in the Abnormal and Normal membership functions for fetal type (Fig. 5) being fully asserted. The simulation has been written to return a type of ambiguous whenever two for more of the clipped membership functions are tied for the maximum, resulting in a bimodal function. This has been done since the physician wants a fuzzy answer, not a degree of normal, abnormal, etc. Due to the sharp slopes of most of the membership functions for head circumference, abdominal circumference and femur length, the probability of obtaining a result of ambiguous is small.

An additional 1,000 cases were evaluated to assess the robustness of the developed fuzzy system. The biometric measurements for each case were obtained by making a draw from a Gaussian distribution with a mean in the center of the bounds in Eqs. (1-3) for head circumference, abdominal circumference, and femur length respectively. The thousand cases were evaluated using the fuzzy infernce system resulting in 95.9% of the cases being identified correctly and only 4.1% being typed as ambiguous. The physician would be required to review the ultrasonic examination and determine the cause of the "ambiguous" result and the true state of the fetus.

5 Conclusion

The use of fuzzy inference systems to assist in the analysis of ultrasonic fetal examinations appears very promising. Fuzzy inference systems can provide a rapid and uniform evaluation of fetal examinations pointing out to the physician areas which require additional review. The inference system developed identified almost 96% of the fetal types correctly with the remainder ambiguous. This paper has presented the first successful investigation into a promising research area. We are currently pursuing this project further in the following areas:

(i) Development of Signal Processing/fuzzy algorithms to segment raw ultrasonic images.

(ii) Work with the medical community to refine membership functions.

(iii) Work with the medical community to develop exhaustive rule set.

(iv) Development and testing of a prototype system.

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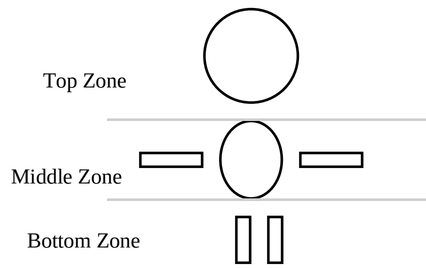

Figure 1: Example of a segmented fetal image to be analyzed.

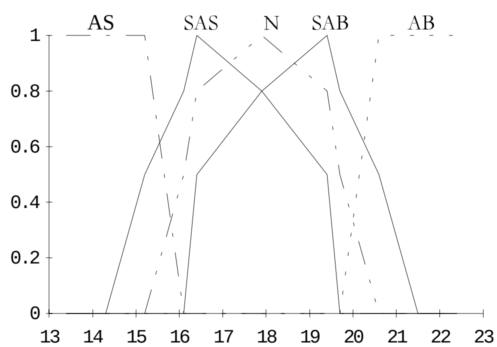

Figure 2: Membership functions for head circumference *H* for a 20 week old fetus.

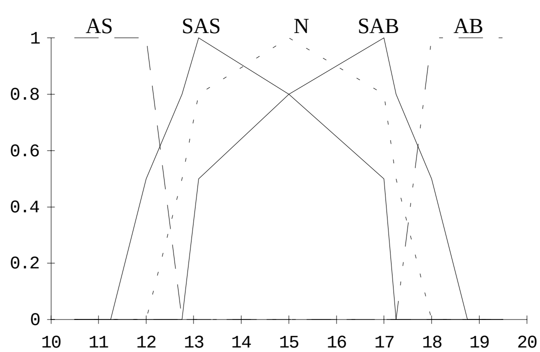

Figure 3: Membership functions for abdominal circumference *A* for a 20 week old fetus.

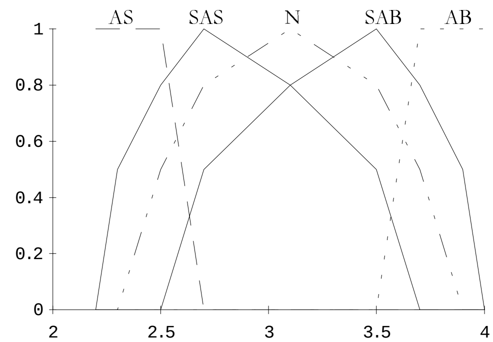

Figure 4: Membership functions for femur length F for a 20 week old fetus.

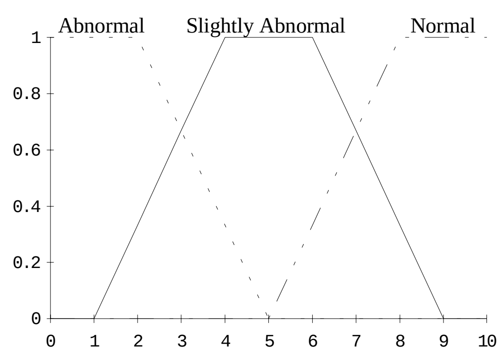

Figure 5: Membership functions for normal (N), slightly abnormal (SAB), and abnormal fetuses (AB).