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IMPROVING THE EFFICIENCY OF FETAL-EMOTION CLASSIFICATION USING HYBRID FEATURE DESCRIPTORS

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Abstract— **Fetus facial expression analysis is a recent and upcoming field of study in the area of biomedical image processing. Fetus images are obtained using 3D ultra-sounds, and thus there is minimum clarity in terms of the fetus face alignment, the fetus face posture and the fetus face size. All these issues make it a challenging task to identify the location of fetus face, and thus the fetal expression becomes a complicated task. In this paper, a saliency map based method is used to segment out the fetus face. Harries algorithm and surf feature detection algorithm are used for feature extraction with good level of accuracy, and then identify the fetus emotion using a recurrent neural network based classifier. Our work shows more than 80 % accuracy.**

Keywords— ***Color map, fetal facial expression, fetus mood, face, harries algorithm, saliency map, recurrent NN, shape map***.

I. INTRODUCTION

Fetal facial expression analysis is a field of study in the biomedical image processing. In this field, the sonographs obtained during pregnancy are analyzed so that the fetus condition can be evaluated. The development of three-dimensional (3D) and four-dimensional ultrasound (4D) has provided new opportunities to study fetal and even embryonic behavior the principal. The study of fetal nervous system has been a great challenge for obstetricians and neonatologists for many years. fetal behavioral patterns directly reflect developmental and maturation processes of fetal nervous system.

Fetal scans have shown that fetuses develop expressions from 24 weeks, these expressions can range from smile to crying, based on the fetus mood . This continuous process, helps doctors to identify issues with the fetus [2]. These expressions are also an indicative of the fetus good health, and are continuously monitored by doctors with the help of 3D and 4D ultra-sound scans [3].Kurjak et. al. Gynecologist [4] proposed, a novel observational based algorithm named KANET that uses 4D ultrasound scans to check the fetus mood. In this test, the general movements (GM) are recorded and observed. The KANET test has the potential to detect and discriminate normal from borderline and abnormal fetal behavior in normal and in high risk pregnancies, which means that it could become a valuable diagnostic tool for fetal neurological assessment. review and analyze the published literature on the use of 3D and 4D ultrasound in the assessment of fetal behavior.The KANET test was standardized order for the test to become reproducible and can be easily applied by fetal medicine specialists [5].Miskovic et al applied KANET in 226 cases, both high and low risk pregnancies and compared the results. The authors concluded that these preliminary results were promising and stated that further studies are needed before the test could be recommended for wider clinical practice [1, 6].

In our case, we used the saliency map technique for pre-processing and segmentation of the fetus face image. The saliency map uses a visual attention model, and evaluates the regions which are of utmost importance from the input image, and then extracts those regions in order to segment out the image. The segmented face (in our case), is given to a feature extracted unit, wherein we have used the harries algorithm . Recurrent Neural Network is used for classification.

II. PROPOSED SYSTEM

The input is taken by the 3D ultrasound images, which are captured by ultrasound equipment's. Generally the sonography images are of JPEG format. The processing unit uses extended color map and extended edge map to evaluate features of the image and then performs recurrent neural network (NN) training using the training data as shown in fig.1. The trained recurrent NN is then used in real time to evaluate the mood of the fetus. The algorithm is divided into the following steps

A. Image Segmentation using Saliency Map Technique

The input image is first segmented using a quaternion based saliency map technique. Saliency maps are used for segmentation due to the fact that for a fetus image, the facial area is the most visually appealing region. Thus, it does a

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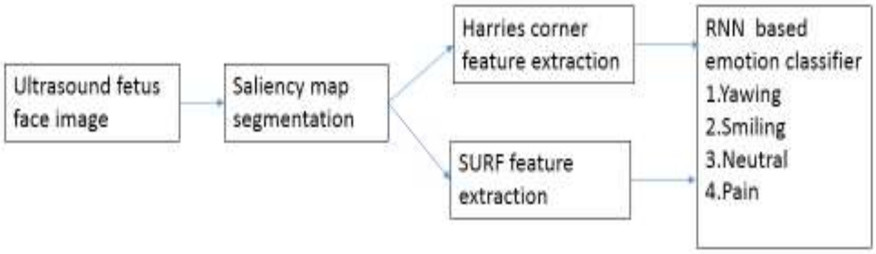

Fig. 1. Block diagram of the proposed system

perfect job at extracting the facial components from the image, and removing all the other unwanted regions from it.

It can be seen from fig.2 that the saliency map extracts all the visually important information from the fetus imagery.

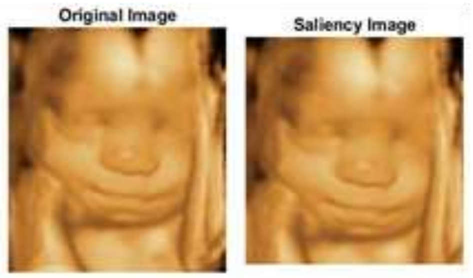

Fig.2. Results of Saliency map on fetus images

The saliency map algorithm, divides the image into R, G and B components, then applies a quaternion technique to represent the pixels in a 3D region. These pixels are then smoothened using a gaussian filter. The smoothened pixels are given to an entropy calculation block, which finds out the best energy pixels from the given set. The best energy pixels when combined, form the rough saliency map. This rough saliency map is again smoothened using the gaussian filter, and then given to a border cutting and center biasing block, which removes all the unwanted edges from the image and produces a final saliency map image, as shown in fig.2.

For evaluating the saliency map, first a color image is resized to a coarse 64 x 48 pixel representation. Then, for each color channel xi , the saliency map is formed from the image reconstructed from the image signature using the following equation,

$$m = g * \sum x{-}i\dot{o}\, x{-}i \qquad (1)$$

where, g is the standard deviation of the Gaussian blurring kernel. For the choice of color channels, we use both RGB and CIELAB color spaces. In the following sections, the algorithms associated with these choices will be referred as RGB-Signature and LAB Signature, respectively.

B. Harris corner Feature detection

In this work, we present an unsupervised method, Harris detector [7] as interest points for several advantages, such as robust to geometric transformations, cclusions and the reliability of information.A point is considered as an interest point if:

This point is defined as the center of a region.A function of interest is maxima in comparison with neighboring regions. Harris detector use the auto-correlation matrix as a function of interest. According to the theory of Harris corner detection, by sweeping a window on image, the gray intensity change can be expressed by the following expression

$$E(u,v) \approx [u,v]\ M \begin{bmatrix} u \\ v \end{bmatrix}$$

1

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x{}^2(x,y) & I_x(x,y) I_y(x,y) \\ I_x(x,y) I_y(x,y) & I_y{}^2(x,y) \end{bmatrix}$$

2

w(x,y): the window function for smoothing, generally the gaussian window is used.

Ix, Iy: derivatives in x and y directions respectively.

A large variation of E in all directions signify a corner.

Mathematically, the exact computation of eigen values of matrix M is very expensive. Harris and Stephens use det(M) and trace(M) "Equation 3" to avoid computation and find interest points (corners):

$$R = \det(M) - k\big(trace(M)\big)^2$$

3

$$\det(M) = \lambda_1 * \lambda_2 = I_x{}^2(x,y) * I_y{}^2(x,y) - I_x(x,y) I_y(x,y)^2$$

$$trace(M) = \lambda_1 + \lambda_2 = I_x{}^2(x,y) + I_y{}^2(x,y)$$

k: an experience value, usually selected from the interval [0,04:0,06].

We slid window in the image document, then, the interest points of Harris [7] are extracted from each region in the image to represent and to compare the query with this regions.In “Fig. 3,” we give an illustration of detected interest points form a region in the image document.

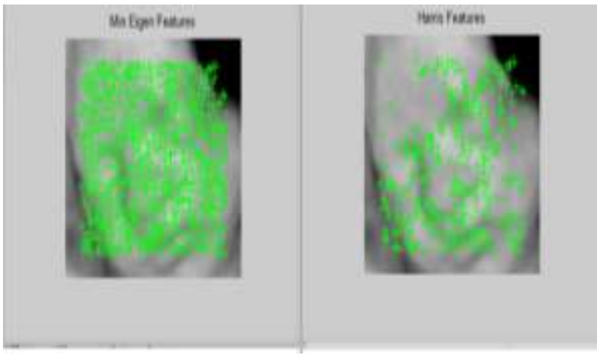

Fig.3. Results of Harris map on fetus images

C. SURF Feature descriptor

Although SIFT algorithm is considered the most effective, but without the help of the hardware to speed up, common computer conditions are hard to reach the real-time level. Aim at the computational complexity of SIFT algorithm, Bay puts forward SURF (Speeded Up Robust Features) algorithm, SURF processing speed is three times faster than SIFT , but the stability has not down too much because it is the simplified and approximated. Generally speaking, SURF is better than SIFT .SURF algorithm basically has the following steps:

SURF feature points detection method is based on scale space theory, it uses the determinant of Hessian matrix as a discriminant to look for local maximum value. Bay, who proposed using the box filter approximate instead of second-order Gaussian filter [8]. With the integral image described in [10] to speed up the convolution to improve the
Computing speed. Further solving and getting the Hessian matrix Δ expression: The descriptor can be divided into two distant tasks: orientation assignment and descriptor components. The procedure for extracting the descriptor is explained further in the following.

1. Orientation assignment

It needs assign a reproducible orientation for each interest point to achieve invariance to image rotation. It’s also important for the extraction of the descriptor components. To determine the orientation, Haar wavelet responses of size 4σ are calculated fora set pixels within a radius of 6σ of the detected point, where σ refers to the scale at which the point was detected. The specific set of pixels is determined by sampling those from within thecircle using a step size of σ. The responses are weighted with a Gaussian centered at the interest point. At each position, the x and y responses within the segment are summed and used to form a new vector. The longest vector lends its orientation the interest point.For the extraction of the descriptor, the first step is to construct a square window centered around the interest point. This size of the window is 20 (σ refers to the detected scale). Furthermore the window is oriented along the direction found in the previous section. The descriptor window is divided into 4 × 4 regular sub-regions.

2. SURF descriptor components

For the extraction of the descriptor, the first step is to construct a square window centered on the interest Point. This size of the window is 20σ (σ refers to the detected scale). Furthermore the window is oriented along the direction found in the previous section. The descriptor window is divided into 4 × 4 regular sub-regions each sub-region has a four-dimensional descriptor vector v.

$$V_{SURF} = (\Sigma d_x, \Sigma d_y, \Sigma |d_x|, \Sigma |d_y|)$$

4

Fig 4. Results of SURF Feature detector

D. Machine learning classifier RNN

The machine learning classifier RNN is trained with the edge maps and color maps of images. As system designers, we trained the RNN for images taken at various angles, different distances and various moods. These trained images determine the mood of σthe fetus under observation. The training set consists of bulk of images and their respective mood values. The recurrent NN is a combination of multiple single NNs, each of the networks have different number of neurons in each of the layers, these different layered networks are connected in parallel and classification results are taken from each of these networks in order to get the final class for the fetus mood.

Recurrent neural networks, like feedforward layers, have hidden layers. However, unlike feedforward neural networks, hidden layers have connections back to themselves, allowing the states of

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the hidden layers at one time instant to be used as input to the hidden layers at the next time instant. This provides the aforementioned memory, which, if properly trained, allows hidden states to capture information about the temporal relation between input sequences and output sequences.

RNNs are called recurrent because they perform the same computation (determined by the weights, biases, and activation functions) for every element in the input sequence. The difference between the outputs for different elements of the input sequence comes from the different hidden states, which are dependent on the current element in the input sequence and the value of the hidden states at the last time step. In simplest terms, the following equations define how an RNN evolves over time,

$$o^t = f(h^t; \emptyset)$$
5

$$h^t = g(h^{t-1}, x^t; \emptyset)$$
6

where o^t is the output of the RNN at time t, x^t is the input to the RNN at time and is the state of the hidden layer(s) at time t. The image below outlines a simple graphical model to illustrate the relation between these three variables in an RNN's computation graph.

The first equation says that, given parameters $\emptyset$ (which encapsulates the weights and biases for the network), the output at time t depends only on the state of the hidden layer at time , much like a feed forward neural network. The second equation says that, given the same parameters, the hidden layer at time t depends on the hidden layer at time and the input at time t. This second equation demonstrates that the RNN can remember its past by allowing past computations to influence the present computations. The developed system is tested under various real time conditions and the results are mentioned in the next section.

III. RESULTS

We tested the system on various 3D fetal ultrasound images, collected from website [9] and obtained some very interesting results. In our experiment, we took images of different fetus moods, and found the following results as given in table II. Thus, we first trained the system with 10 entries, and evaluated it with 12 images, wherein 10 images were trained and 2 images were untrained.

Table I. Accuracy of proposed work using harries algorithm

Number of images used for testing	Accuracy (%) proposed system
10	73.00
20	75.00
30	79.00
50	80.00
75	88.00
100	86.00
200	86.00

Table II shows the comparison of accuracy by using SURF method, Harries feature method and communed method.

Table II. Accuracy for Fetal expressions

Fetus expressions	Number of images tested	Accuracy (%) By SURF Method	Accuracy (%) By Harries Method	Accuracy (%) combined proposed system
Pain	13	70	72.62	76
Neutral	103	82.23	85.15	88.23
Yawning	53	79	80	84.68
Smile	55	82	82.27	84

The system can be further applied to any kind of fetus based processing systems for better accuracy than conventional classifiers.

IV. Conclusion

The proposed system is tested under various conditions SURF algorithm which reduces the running time for extraction of feature points, at the same time, the improved Harris sub-pixel corner detection algorithm is used to detect the position of image features in the image. We plan to further extend this work for getting better accuracy via a self-learning Artificial Intelligence based system which will be used to adaptively learn to read the features and select them in order to get maximal accuracy from the system under test.

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