PLACENTAL MATURITY EVALUATION VIA FEATURE FUSION AND DISCRIMINATIVE LEARNING

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ABSTRACT

In this paper, we propose a new method to evaluate the plac ental maturity. Firstly, we extract both the gray-scale intensi tyfrom B-mode ultrasound (US) images and blood flow info rmation from color Doppler energy (CDE) imagesby the vis ual feature detector and descriptor. After fusing information, we apply the feature encoding method, a multi-layout fisher vector (MFV), to improve the staging performance. Experi mental results show that the proposed method has achieved promising performance for placental maturity staging and o utperformed the traditional methods.

***Index Terms*—**Placental maturity evaluation, Feature fusion, Multi-layout Fisher vector, Color Doppler energy imaging

1. INTRODUCTION

Over the past decades, ultrasound (US) imaging has been extensively applied in prenatal diagnosis and prognosis [1, 2]. The routine placental evaluation is mainly based on US images.Placenta is an important approach to prevent small gestational age (SGA), stillbirth, and pregnancy complications [2].In fact, the placental size, umbilical cord and cord blood flow has close relationship with the placental development during pregnancy. Until now, the prenatal ultrasound examination has played an important role in fetal function evaluation, and hence it has attracted moreand more interest [1-6]. However, most of the existing methods of placental evaluation depend on doctor’s subjective measurement.

To develop objective measurement, B-mode grayscale US imaging has been widely applied in prenatal examinations especially for functional evaluation of placental abnormalities for it can display the calcification degree of the placenta. The traditional way to evaluate the placenta maturity is based on grayscale US image only. For example, Grannum*et al*. proposed the first placental evaluation based on gray-scale image [4] and provided a benchmark tool for placental function evaluation guideline. However, this method still suffered from low reproducibility and generalizability. In [5], Lei *et al.* proposed the placental evaluation based on fisher vector (FV) and invariant descriptor, and achieved promising grading performance. In [6], Li *et a*l. proposed to use dense descriptor such as DAISY to address the placental evaluation problem. This dense sampling method outperformed the traditional covariant affine detectors such as Harris, Hessian, and multi-scale Harris.

Although good performance has achieved in placental evaluation with B-mode gray-scale US images, it was argued that this method is limited and undesirable without blood flow information. To this end, blood vessels have played an important role in placental function evaluation since non-branched and branched blood vessels are essential in morphogenesis during pregnancy [7-9]. Meanwhile, it is known that color Doppler energy (CDE) imaging is a technique to obtain the velocity distribution of blood flow in the human body tissue plane in the form of gray scale or color bands. This technique can learn information to understand not only the structure of human tissue, but also the body's blood flow (or organization) kinematic information. In Doppler imaging, the vessels that are traveling within the region of interest can form the flow spectrum shape and provide flow information. Since there are a large number of visible blood vessels within the placenta after 14 weeks of pregnancy, placental blood vessels detection and blood flow information are particularly important for fetal placental development and evaluation. Therefore, by exploring blood flow information using CDE can enhance placental evaluation. So we propose to incorporate CDE imaging as auxiliary information for prenatal ultrasound examination.

Specifically, we apply visual feature descriptor to extract the useful features from the interest point. After feature extraction, we perform feature encoding to improve the staging performance by high-level information. Since there is redundant and indiscriminative information in the US images, discriminative feature encoding is highly desirable [10]. The commonly applied feature encoding techniques including bag of visual words(BoVW) [11], vector of locally aggregated descriptor(VLAD) [12], and Fisher vector (FV) [13, 14]. Although FV has the ability to learn discriminatively with high-order statistics, the discriminative power is still limited due to the low-resolution US images. To address this problem, we partitioned the original image into small

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sub-divisions to boost the staging performance. Namely, we propose a multi-layout FV (MFV) method instead of traditional FV to obtainspatial information to improve the staging performance.

The main aim of this study is to evaluate placental maturity via fusion of B-mode US and CDE images based on discriminative feature encoding method. The main contribution of this paper are mainly threefold: 1) we integrate the B-mode US and CDE for placental evaluation; 2) we apply the visual descriptor and discriminative learning to evaluate the placental maturity; 3) MFV is developed to integrate spatial information. This research is vital to the placental prognosis and diagnosis for the placental evaluation.

2. METHODOLOGY

2.1. System overview

For the placental maturity evaluation, the original collected US images are first pre-processed (i.e., noise reduction and region of interest extraction), which is shown in Fig. 1. Fig. 2 shows the staging system to evaluate placental maturity automatically with both B-mode US and CDE images. After pre-processing, the interest point is detected by difference of Gaussian (DoG), the visual feature descriptor such as scale invariant Fourier transformation (SIFT), patch, fusion of both are applied to extract the informative features. We exploit the traditional bag of feature. We exploit the traditional bag of feature mechanism to build a vocabulary based on the extracted visual features. Also, we apply feature encoding method to improve the discriminability based on the clustering means and standard deviations. FV extracts the first and second order information to enhance the placental maturity evaluation result via discriminative learning. By clustering representatives, the occurrence count of the visual features in terms of histogram represents the input images. We also apply the same procedure for the testing stage. Support vector machine (SVM) outputs the final decision for grading the placentalmaturity.

2.2. Feature encoding

It is known that BoVW is a simple count of feature distribution represented by the first moment information (i.e., cluster means), and VLAD keeps both mean and residual information. Compared with these two methods, FV is a special case of the traditional methods by incorporating high order information using the Fisher kernel. We encode local image features in a format suitable for learning and comparison with simple metric such as the Euclidean distance Inspired by the promising performance of FVin [13]for object recognition and classification task, we investigate FV as a global feature encoding method to pool local image features to represent the placental image. To enhance the staging performance, we first implement a generative model

Fig. 1. Input US images for placental evaluation; from left to right, original B-mode US gray-scale image, pre-processed B-mode US gray-scale image; original CDE image, pre-processed CDE image.

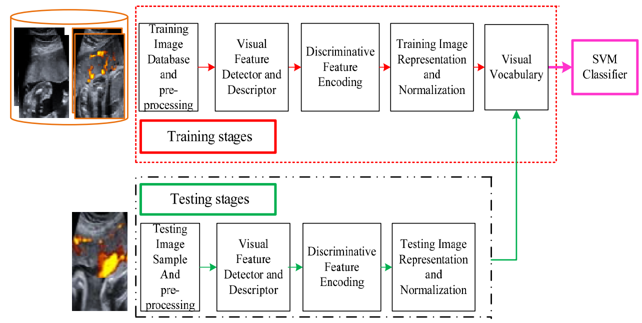


Fig. 2. System overview of the automatic placental maturity staging method.

based on Gaussian mixture model (GMM) to obtain the posterior probability to improve the discrimination ability of FV. Specifically, we extract a set of dimensional feature vectors (e.g., SIFT descriptor) from an image fitted by GMM, and then obtain the parameters in GMM such as the mean and covariance. We incorporate these parameters in FV to increase the staging discriminability. We obtain the first and second order derivatives between dense features and GMM centers as:

$$\Phi_k^{(1)} = \frac{1}{N\sqrt{w_k}} \sum_{m=1}^{N} \gamma_m(k) \left(\frac{x_m - \mu_k}{\sigma_k} \right) \quad (1)$$

$$\Phi_k^{(2)} = \frac{1}{N\sqrt{2w_k}} \sum_{m=1}^{N} \gamma_m(k) \left(\frac{(x_m - \mu_k)^2}{\sigma_k^2} - 1 \right) \quad (2)$$

where w_k, μ_k, σ_k are the GMM mixture weights, means, and diagonal covariance, $\gamma_m(k)$ is the soft assignment weight of the *m*-th feature x_m to the *k*-th Gaussian. By concatenating the vectors together, we obtain: $\phi_{FV}(x_m) = [0,...,0,\underbrace{\Phi_k^{(1)},\Phi_k^{(2)}}_{2D\ non-zeros},0,...,0]$ for feature representation via FV, which include high order statistics.

2.3. Multi-layout Fisher vector

It is noted that spatial relationships among local appearances play an essential role in recognizing the US image underlying structures. Different from the previous studies, we also incorporate the spatial information to boost the performance. Namely, we divide the input image into different divisions to extract dense features with multi-layout strategy. It gains an advantage of single information from only one subdivision. Therefore, we apply the partitioning technique to extract features. The visual word occurrence from each partition is appended to form the spatial layout of MFV, which is the main difference between our method and the previous FV method. Fig.3 shows the proposed MFV method with 2×2 layout. We divide the image into sub-divisions to incorporate spatial distribution information. We built the feature vectors by concatenating all features in every division. Evidently, MFV is a concatenation of different layers to incorporate all information. MFV increases the discriminability of the descriptor using spatial information.

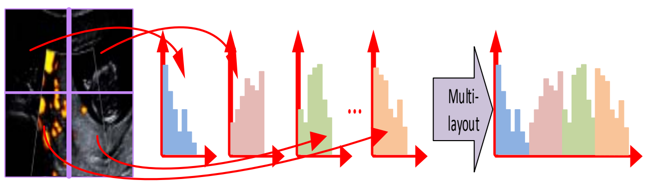


Fig. 3.Pipeline of the proposed multi-layout FV (MFV) algorithm. Original US image is partitioned into sub-divisions. Features are extracted by the visual descriptor from each division, and then concatenated to form the image representation

3. EXPERIMENT RESULTS

3.1. Experiment setup

To assess the placental function evaluation, we carry out experiments to evaluate the placental maturity performance. We obtain the input images from a commercial US scanner (Acuson S2000, Siemens Medical Solutions, USA) from Shenzhen Maternal and Child Health Hospital. A total of 544 placental images from both B-mode US and CDE images were acquired. The images are composed of 200 B-mode US and 11 CDE images with stage 0, 147 B-mode US and 7 CDE images with stage I, 105 B-mode US and 22 CDE images with stage II, 44 B-mode US and 8 CDE images with stage III. We split our training and testing samples using 10-
fold cross validation strategy, namely, 10 % of total samples are used for training images and 90% of them are used for testing images. The routine examines with the traditional US sweep were performed for placental evaluation by more than 5-year experienced radiologists in obstetrics. The quantitative methods include accuracy (ACC), sensitivity (SEN), specificity (SPEC), mean average precision (mAP), area under receiver operation characteristics (AUC), and receiver operating characteristic (RoC) curves. The calculation of the performance evaluation metrics is the same as thatin [6]. The typical training images in each stage with both B-mode US and CDE are shown in Fig. 4.

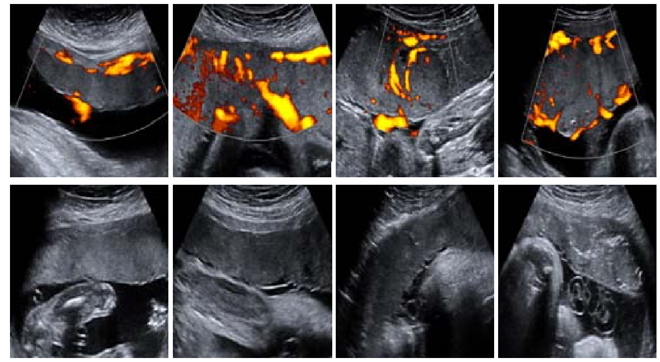


Fig. 4. Image samples of 4 stages (from left to right, stage 0 to stage III).

3.2. Placental function evaluation results

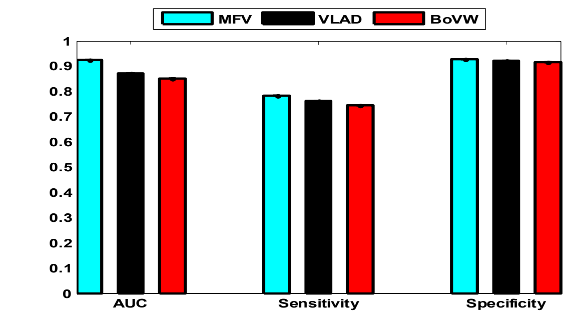
Table 1 shows mAP, SEN, SPEC and ACC of the placental function evaluation based on different feature encoding methods and descriptors. It can be seen that the fusion method (the combination of both SIFT and patch information) with multi-layout technique achieved the best performance for placental function evaluation. Also, the performance of placental function evaluation with multi-layout algorithm outperformed that without the multi-layout technique. The best mAP, SEN, SPEC and ACC results for fusion method with multi-layout are 0.973, 0.911, 0.976, and 0.927, respectively, which demonstrated the effectiveness of the proposed method for the placental function evaluation. The main reason is that the high order statistics learned by FV are suitable and effective for the placental staging. Moreover, the obtained high staging result of the proposed method demonstrates the potential practical application in the clinical practice. Fig. 5 shows RoC results obtained by various feature encoding methods based on fusion method to further validate the effectiveness of the proposed method. It is clear that the MFV outperforms traditional VLAD and BoVW methods.

4. CONCLUSIONS

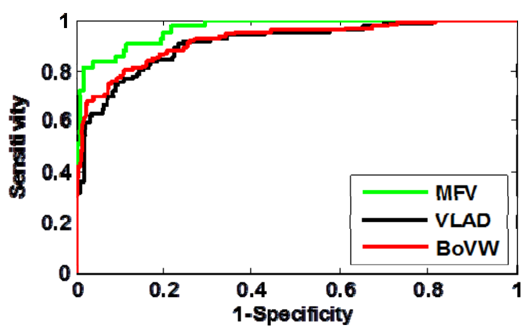
In this paper, we propose a new method for placental maturity evaluation based on both B-mode US and CDE images. We develop a multi-layout method for feature encoding to integrate the spatial information. Extensive experimental results demonstrated that our proposed method has obtained remarkable performance in placental function evaluation. We found that feature fusion is effective for the fetal placental maturity function evaluation. By automatic staging algorithm, it is able to provide effective diagnosis assistance for clinicians and pave the way for placental maturity evaluation.

Table 1.*Placental maturity evaluation results.*

Encoding	Descriptor	Without multi-layout (1×1)				With multi-layout(2×2)			
		mAP	**SEN**	**SPEC**	**ACC**	**mAP**	**SEN**	**SPEC**	**ACC**
BoVW	Patch	0.670	0.531	0.879	0.636	0.786	0.697	0.921	0.764
	SIFT	0.757	0.628	0.897	0.691	0.754	0.680	0.927	0.782
	Fusion	0.837	0.770	0.915	0.746	0.820	0.716	0.915	0.746
VLAD	Patch	0.862	0.680	0.927	0.782	0.904	0.708	0.939	0.818
	SIFT	0.901	0.803	0.952	0.855	0.948	0.727	0.946	0.836
	Fusion	0.918	**0.833**	0.946	0.836	0.951	0.763	0.946	0.836
FV	Patch	0.912	0.789	0.946	0.836	0.919	0.776	0.946	0.836
	SIFT	**0.934**	0.828	**0.964**	**0.891**	0.929	0.777	0.952	0.855
	Fusion	0.920	0.769	0.932	0.796	**0.973**	**0.911**	**0.976**	**0.927**



(a)



(b)

Fig.5. Staging results of feature encoding methods in terms of fusion technique; (a) AUC, sensitivity, specificity results of different feature encoding methods; (b) RoC curves of different feature encoding methods.

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