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PCA- Based Feature Extraction and LDA algorithm for Preterm Birth Monitoring

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Abstract. **Most pregnancies last around 40 weeks. Babies born between 37 and 42 completed weeks of pregnancy are called full term. Premature birth is a serious health problem. Premature babies are at increased risk for newborn health complications, such as breathing problems, and even death. Most premature babies require care in a newborn intensive care unit (NICU). A preemie usually needs frequent office care – to screen vision or hearing problems and assess baby development – involving multiple medical disciplines which require accurate coordination. Thus, we proposed a monitoring system to classify the behavior of a preemie using intelligent vision system. The focus is on predicting preemie behavior based on preemie motion, face and skin analysis. Our preliminary experimental results show a promising performance of the initial part of the system involving preemie face, skin detection and LDA algorithm.**

Keywords: *Preterm Birtt, Image Processing, PCA, LDA*

1. Introduction

Most pregnancies last around 40 weeks. Babies born between 37 and 42 completed weeks of pregnancy are called full term. Babies born before 37 completed weeks of pregnancy are called premature. In the United States, about 12.8 percent of babies (more than half a million a year) are born prematurely [1]. The rate of premature birth has increased by 36 percent since the early 1980s [1].
Premature birth is a serious health problem. Premature babies are at increased risk for newborn health complications, such as breathing problems, and even death. Most premature babies require care in a newborn intensive care unit (NICU), which has specialized medical staff and equipment that can deal with the multiple problems faced by premature infants.

Premature babies also face an increased risk of lasting disabilities, such as mental retardation, learning and behavioral problems, cerebral palsy, lung problems and vision and hearing loss. Two recent studies suggest that premature babies may be at increased risk of symptoms associated with autism (social, behavioral and speech problems) [2-3]. Studies also suggest that babies born very prematurely may be at increased risk of certain adult health problems, such as diabetes, high blood pressure and heart disease [4]. Preterm infants are at risk for poor growth while in the neonatal

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intensive care unit (NICU) and after discharge from the NICU. They must be closely monitored and may require interventions to promote better growth [5-7]. Thus, the goals of this paper are to promote a normal growth and a development of preemies birth monitoring. A PCA method was employed to study the behavior of the infant. The experimental results reveal that the proposed method can minimize the morbidity and mortality than the conventional method based on LDA algorithm.

2. System Overview

The long-term goal of this research is the development of a stand-alone automated system that could be used as a supplement in the NICU to provide 24-h/day noninvasive. The development of a jaundice-detection system involves the following three tasks: (a) the extraction of PCA feature information from video recordings of infants monitored for jaundice, (b) the selection of quantitative features that convey some unique behavioral characteristics of neonatal jaundice such as mean, standard deviation, skew ness, kurtosis, energy and entropy and (c) validation test to distinguish between jaundice and normal newborn infant. The complete block diagram is shown in Fig.1.

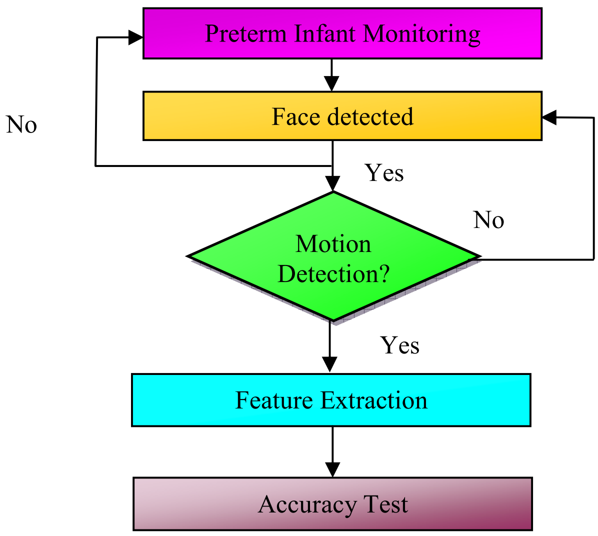

Figure 1. Preterm Infant Monitoring Overview System

3. Preterm Babies Monitoring

This study relied on analog video recordings selected from a random database developed by the [8]. All the acquire images are differ from the illumination level, distance and the angle of the picture taken. This variety of images gives the further experiment more interesting in order to find a robust portion to monitor the infant behavior. The data collection computer configured with MATLAB R2009a and the Image Acquisition Toolbox.

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Figure 2. Newborn are treated in Incubator

4. Face Detection

Based on YCrCb color space, where the advantages are Chroma (CrCb) and luminance (Y) information is stored in different channels due to working process are involving with different lightning conditions [9]. It seems that lighting information could easily lead to false detections, hence the luminance component need to be discarded. In YCbCr color space it is simply to be done by not using one of its channels according to [10].The result of Face Detection is first processed by a decision function based on the Chroma components CrCb from YCrCb and Hue from HSV by [11] creating a Skin Map. If all following conditions are true for a pixel, it's marked as skin area. The image in Fig. 3 below shows a possible result. Skin areas are marked with red box

$$140 < Cr < 165$$
$$140 < Cb < 195$$
$$0.01 < Hue < 0.1$$

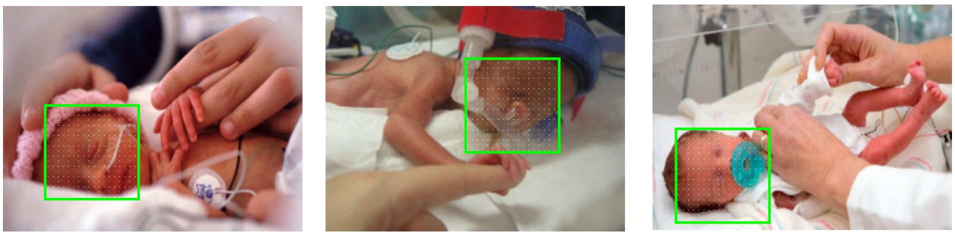

Figure3. Face Detection results

5. Principal Component Analysis

Principal Component Analysis (PCA) [12] is a standard technique for dimensionality reduction and has been applied to a broad class of computer vision problems, including feature selection (*e.g.,* [13]), object recognition (*e.g.,* [14]) and face recognition (*e.g.,* [15]). While PCA suffers from a number of shortcomings [16, 17], such as its implicit assumption of Gaussian distributions and its restriction to orthogonal linear combinations, it remains popular due to its simplicity. The idea of applying PCA to image patches is not novel (*e.g.,* [18]). Our contribution lies in rigorously demonstrating that PCA is well-suited to representing key point patches (once they have been transformed into a canonical scale, position and orientation), and that this representation significantly improves premature detection performance as discuss in Chapter 7

6. LDA Algorithm

The basic idea of LDA is to find a linear transformation such that feature clusters are most separable after the transformation. This can be achieved through scatter matrix analysis [19]. For an M-class problem, the between and with in class scatter matrices S_b and S_w are defined as:

$$S_b = S_b = \sum_{i=1}^{M} P\tau(C_i)(\mu_i - \mu)(\mu_i - \mu)^T = \Phi_b \Phi_b{}^T, \quad (1)$$

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$$S_w = \sum_{i=1}^{M} P\tau(C_i) \sum{}_i = \Phi_w \Phi_w{}^T, \tag{2}$$

Where $P\tau(C_i)$ is the prior probability of class (C_i) and usually is assigned to $\frac{1}{M}$ with the assumption of equal priors; μ is overall mean vector; $\sum_i$ is the average scatter of the sample vectors of different classes (C_i) around their reprehensive mean vector μ_i:

$$\sum{}_i = E\left[(x-\mu_i)-(x-\mu_i)^T \middle| C-C_i\right] \tag{3}$$

The class separately can be measured by a certain criterion. A commonly used one is the ratio of the determinant of the between class scatter matrix of the projected samples to the within class scatter matrix of the projected samples:

$$(A) = \arg\max \frac{\left|AS_bA^T\right|}{\left|AS_wA^T\right|} \tag{4}$$

Where A is an *m x n* matrix with (*m* ≤ *n*). A solution to the optimization problem of Equation (4) is to solve the generalized Eigen value problem [20]:

$$S_bA^* = \lambda S_wA^* \tag{5}$$

$$D_i(X) = A^{*T}(X-\mu_i), i = 1,2,....,m. \tag{6}$$

A solution to Equation (5) is to compute the inverse of S_w and solve a Eigen problem for matrix $S_w{}^{-1}S_b$ [17]. But this method is numerically unstable because it involves the direct inversion of a likely high dimensional matrix. The most frequently used LDA algorithm in practice is based on simultaneous diagonalizable [19]. The basic idea of the algorithm is to find a matrix A that can simultaneously diagonalizable both S_w and S_b, i.e.

$$AS_wA^T = I, AS_bA^T = \Lambda \tag{7}$$

Where Λ is a diagonal matrix with diagonal elements sorted in a decreasing order. If we want to reduce dimension of the matrix from *n* to *m*, we can simply use first *m* rows of A as the transformation matrix, which corresponds to the largest *m* Eigen values of Λ. The simultaneous diagonalization algorithm also involves inversion of matrix. To our knowledge, most algorithms require that the within class scatter matrix be S_w nonsingular, because the algorithms diagonalizable S_w first. Such a procedure breaks down when the within class scatter matrix S_w becomes singular. This can happen when the number of training samples is smaller than the dimension of the sample vector. This is the case for most face recognition tasks. For example, a small size of image of 64x64 turns into a 4096dimensional

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vector when set vectors. The solution to this problem is to perform two projections [21, 22, 23, 24, and 25].

7. Results and Discussion

The proposed algorithm was evaluated on a hundred and twenty subjects with different race, gender and age. The average size of each image is 400-500 pixels. The entire subjects were tested for ten trials. Ten images were taken for each subject. Average accuracy for all subjects was shown in Table1.

Trial	*Accuracy Detection %*
1	88.22
2	88.33
3	90.12
4	90.43
5	91.35
6	91.65
7	92.34
8	93.85
9	94.95
10	

Table 1. Accuracy Detection Based on PCA and LDA Algorithm

The confidence values for the recognition of a person is calculated using the Euclidean distance between the PCA projected values of the test image and PCA projected values of the train database. This value determines whether recognition of a face image using this method is dependable or not. When the confidence value is low recognition is not dependable. The confidence value obtained for different test images are tabulated in Table I.

8. Conclusion

The proposed preterm monitoring algorithm localizes the face from the given input image using the Color Detection meth. The detected face image is projected using Eigen face analysis and classified using the Linear Discriminant Analysis (LDA) classifier. This algorithm is efficient as it can be integrated with the output from multi-modal sensors and thus can be used as part of multi-sensor data fusion.

9. References

[1] Martin, J.A., et al. Births: Final Data for 2006. National Vital Statistics Reports, volume 57, number 7, January 7, 2008.
[2] Limperopoulos, C., et al. Positive Screening for Autism in Ex-Preterm Infants: Prevalence and Risk Factors. Pediatrics, volume 212, number 4, April 2008, pages 758-765.
[3] Schendel, D., and Bhasin, T.K. Birth Weight and Gestational Age Characteristics of Children with Autism, Including a Comparison with Other Developmental Disabilities. Pediatrics, volume 121, number 6, June 2008, pages 1155-1164.
[4] Hovi, P., et al. Glucose Regulation in Young Adults with Very Low Birthweight. New England Journal of Medicine, volume 356, number 20, May 17, 2007, pages 2053-2063.
[5] Ehrenkranz RA, Younes N, Lemons JA, et al. “Longitudinal growth of hospitalized very low birth weight infants”, Pediatrics; 104:280,1999.

[6] Lemons JA, Bauer CR, Oh W, et al. "Very low birth weight outcomes of the National Institute of Child health and human development neonatal research network, January 1995 through December 1996". NICHD Neonatal Research Network Pediatrics; 107:E1.2001
[7] Blackwell MT, Eichenwald EC, McAlmon K, et al. " Interneonatal intensive care unit variation in growth rates and feeding practices in healthy moderately premature infants", J Perinatol; 25:478, 2005.
[8] http://www.google.com/search
[9] Mansor MN, Yaacob S, Nagarajan R, Muthusamy H: "Patients Tremble Analysis under different Different Camera Placement in Critical Care" International Journal of Research and Reviews in Soft and Intelligence Computing (IJRRSIC), Vol 1, No 1, pp, 1-4, Science Academy Publisher, (2011)
[10] Mansor MN, Yaacob S, Nagarajan R, Muthusamy H: "Patients Facial Expressions Analysis under different angle in Intensive Care Unit" Signal & Image Processing: An International Journal (SIPIJ), NnN Net Solution Private Ltd (2011)
[11] Mansor MN, Sazali Yaacob, R.Nagarajan, M Hariharan. "Patient Monitoring for Hospital ICU Patients under unstructed lighting" in *IEEE Symposium on Industrial Electronics & Applications (ISIEA 2010),* Penang, Malaysia, October, 2010
[12]I. T. Joliffe. *Principal Component Analysis*. Springer-Verlag, 1986.
[13]K. Fukunaga and W. Koontz. Application of the Karhunen-Loeve expansion to feature selection and ordering. *IEEE Trans. Communications*, 19(4), 1970.
[14]H. Murase and S. Nayar. Detection of 3D objects in cluttered scenes using hierarchical eigenspace. *Pattern Recognition Letters*, 18(4), April 1997.
[15]M. Turk and A. Pentland. Face recognition using eigenfaces. In *Proceedings of Computer Vision and Pattern Recognition*, 1991.
[16]J. Karhunen and J. Joutsensalo. Generalization of principal component analysis, optimization problems and neural networks. *Neural Networks*, 8(4), 1995.
[17]D. Lee and S. Seung. Learning the parts of objects by non-negative matrix factorization. *Nature*, 401, 1999.
[18]R. Fergus, P. Perona, and A. Zisserman. Object class recognition by unsupervised scale-invariant learning. In *Proceedings of Computer Vision and Pattern Recognition*, June 2003.
[19]K. Fukunaga. *Introduction to Statistical Pattern Recognition(Second Edition)*. New York: Academic Press, 1990.
[20] S. S. Wilks. *Mathematical Statistics*. New York: Wiley, 1962
[21] D. Swets and J.Weng. Using discriminant eigenfeatures for image retrieval. *PAMI*, 18(8):831–836, August 1996.
[22] P.Belhumeur, J.Hespanha, andD.Kriegman.Using discriminant eigenfeatures for image retrieval. *PAMI*, 19(7):711– 720, 1997.
[23] K. Etemad and R. Chellappa. Discriminant analysis fo recognition of human face images. *Journal of the Optical Society of America A*, 14(8):1724–1733, 1997.
[24] W. Zhao, R. Chellappa, and P. Philips. *Subspace LinearDiscriminant Analysis for Face Recognition*. Technical Repor CARTR914 Center for Automation Research, University of Maryland, 1999.
[25] Y.Jie, H.Fei, K.William , "*An Efficient LDA Algorithm For Face Recognition".*In 6th International Conference on Control, Automation, Robotics and Vision 2000, ICARCV 2000.