Down syndrome detection based on facial features using a geometric descriptor

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Abstract. Down syndrome is one of the most common genetic disorders caused by chromosome abnormalities in humans. Among other physical characteristics, certain facial features are typically associated in people with Down syndrome. We investigate the problem of Down syndrome detection from a collection of face images. As the main contribution, a compact geometric descriptor is used to extract facial features from the images. Experiments are conducted on an available dataset to demonstrate the performance of the proposed methodology. © 2017 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: 10.1117/1.JMI.4.4.044008]

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1 Introduction

Dysmorphology is a branch of medicine (more specifically, clinical genetics), in which physicians are involved in the identification of congenital anomalies caused by hundreds of different syndromes.¹ Early and accurate diagnosis of a syndrome is important to the patients and their families, resulting in more effective care. However, it is worth emphasizing that a precise recognition of dysmorphic features depends upon experienced clinicians and health staff, as well as complex laboratory procedures.

The use of computer-aided tools^{2,3} based on image processing and machine-learning techniques can facilitate the recognition of facial dysmorphic features associated with genetic syndromes. By extracting facial points and computing measurements from images, such structural malformations may be automatically identified.

Several genetic disorders present dysmorphic features, for instance, Williams, fragile X, Cornelia de Lange, Down, Dubowitz, Smith–Magenis, Edwards, Russell–Silver, and Prader–Willi syndromes.

Down syndrome is a genetic abnormality that occurs in approximately one per 1000 babies born each year.⁴ The syndrome was described in detail by John Langdon Down in 1866.⁵ Identified by French researchers in 1959, the presence of an extra chromosome 21 causes the genetic disorder.⁶

Several physical and intellectual disabilities are typically associated with Down syndrome;⁷ however, their degree varies from person to person. While some people with Down syndrome may require much support and care, others can live an ordinary life.

Some common characteristics present in people with the disorder include distinctive facial features, such as slanting eyes, small chin, round face, flat nasal bridge, Brushfield spots in the iris, abnormal outer ears, and flattened nose.

There are still few studies available in the literature that investigate the identification of Down syndrome from images. In this work, we propose and analyze a method for Down syndrome detection based on facial features using a geometric descriptor.⁸ This compact descriptor is composed of 14 distances calculated among facial fiducial points.

Experimental results demonstrate that the proposed method is effective to discriminate facial differences from individuals affected by Down syndrome and healthy individuals over a collection of images.⁹ The dataset contains photographs of patients from different ages, genders, and ethnicities, acquired from different angles.

The rest of the paper is organized as follows. Section 2 briefly describes related work available in the literature. Section 3 presents the methodology proposed in this work. Section 4 describes and analyzes the experimental results. Section 5 concludes the paper with final remarks and directions for future work.

2 Background

Landry et al.¹⁰ used mathematical techniques for classifying congenital abnormalities from hand radiographs. Discriminant analysis was used to identify different syndromes from normal conditions.

A computer-based recognition of dysmorphic faces based on a graph-matching algorithm for describing facial patterns was described by Loos et al.¹¹ Gabor wavelets were used to preprocess the photographs and obtain a description of image regions.

A method for identifying among 10 syndromes is presented by Boehringer et al.¹² Gabor wavelet filter was applied to the landmark coordinates extracted from the faces.

Erogul et al.¹³ described a method for detecting Down syndrome in photographs of children. A graph method is constructed from facial points, and a neural network is used in the classification process.

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Table 1 Comparison of some methods for Down syndrome recognition according to accuracy rates (in percentage).

Approach	Strategy	Number of images	Accuracy (%)
Zhao et al. ¹⁸	Geometric and texture features + SVM	48	97.90
Saraydemir et al. ¹⁶	Gabor wavelet transform + PCA + LDA + SVM	30	97.34
Kruszka et al. ¹⁹	Geometric and texture features + SVM	65	94.30
Burçin and Vasif ¹⁵	LBP	107	95.30
Erogul et al. ¹³	Elastic bunch graph matching	86	68.70

Zhao et al.¹⁴ proposed a hierarchical constrained local model based on independent component analysis, which was applied to detect Down syndrome from facial photographs. Local binary patterns (LBPs) were extracted and selected from located landmarks. Different classifiers were used to compare the results of the Down syndrome identification. The LBP descriptor was employed by Burçin and Vasif¹⁵ to identify Down syndrome in face images.

Saraydemir et al.¹⁶ used Gabor wavelet transform as a feature extractor, as well as K -nearest neighbor (K -NN) and support vector machines (SVMs) as classifiers to analyze the effect of training set dimension on the recognition of dysmorphic faces.

David and Lerner¹⁷ described a method for genetic syndrome classification based on the SVM classifier using fluorescence *in situ* hybridization signals. Different SVM kernels were analyzed, where Gaussian kernel provided more accurate results.

Zhao et al.¹⁸ presented a method for detecting Down syndrome in images through the combination of texture and geometric information. An SVM classifier was employed to distinguish between normal and abnormal cases.

Table 1 presents the results for some Down syndrome recognition methods available in the literature. It is worth mentioning that most of the methods report accuracy rates for private datasets.

Fig. 1 Diagram with the main steps of the proposed Down syndrome detection methodology.

3 Proposed Methodology

The proposed methodology for recognition of Down syndrome in face images is composed of four main stages: (i) facial detection, (ii) feature extraction, (iii) feature reduction, and (iv) classification. Figure 1 shows these steps, which are described in more detail in the following subsections.

3.1 Facial Detection

Initially, the Viola–Jones method²⁰ is applied to detect faces in the image collection. The algorithm is based on a machine-learning approach that uses a cascade function trained with positive and negative images. Haar-like features are extracted from windows at multiple scales over an integral image. Relevant features are selected through a variant of Adaboost learning algorithm, where a cascade classifier is composed of several stages, each one containing a classifier that determines if a window contains a face or not. This cascade structure improves the chance of a face being detected. Figure 2(a) shows a detected face.

After a face is detected, Dlib library²¹ is used to extract facial landmarks. The algorithm employs an ensemble of regression trees trained to estimate the landmark positions. A total of 68 points, corresponding to (x, y) coordinates of regions surrounding each facial structure (eyes, eyebrows, mouth, nose, and jaw) are located in the images. Figure 2(b) shows this stage.

3.2 Feature Extraction

In this step, a geometric descriptor is built from the detected facial landmarks. The geometric representation uses 13 2-D facial fiducial points: two points for the middle of the eyebrows (P_1 and P_2), one point for the glabella (P_3), four points for

Fig. 2 Facial detection step: (a) detected face and (b) marked fiducial facial points.

Fig. 3 Feature extraction: (a) and (b) 16 facial landmark detected from the face and (c) 14 distances extracted from the 16 fiducial points.

the inner and outer corner of the eyes (P_4 , P_5 , P_7 , and P_8), one point for the root of the nose (P_6), two points for the alars side-walls (P_{10} and P_{11}), one point for the supratrip (P_9), one point for the columella (P_{12}), two points for the mouth corners (P_{14} and P_{15}), and two points for the top of the upper lip and bottom of the lower lip (P_{13} and P_{16}). Figures 3(a) and 3(b) show the localization of the 16 facial points.

Fourteen distances are extracted from the mentioned 16 points, as shown in Fig. 3(c). These distances are normalized to the face width to ensure the features are scale invariant. The nine distances d_1 , d_2 , d_3 , d_6 , d_8 , d_{10} , d_{11} , d_{12} , and d_{14} represent the average values of the two mirrored distances on the left and right sides of the face. The latter distance d_{11} is calculated using the intersection point of the line between the points on the top of the upper lip and bottom of the lower lip, and the line between the left and right corners of the mouth. Hence, the resulting feature vector has 14 dimensions.

For Down syndrome recognition, it is important to consider the intercanthal distance d_4 , that is, the distance between the inner corners of the eyes. People with Down syndrome often present telecanthus,^{22,23} meaning an increasing of the intercanthal distance. Another common characteristic is the occurrence of small palpebral fissures,²² which is the space between the lateral and medial canthus of the eyes. This feature is captured by distance d_3 . Individuals with Down syndrome frequently present the symptom of flattened nose.²³ Distances d_5 to d_8 represent this characteristic. Finally, another symptom is the presence of a small mouth,²³ whose characteristic is captured by distances d_{10} to d_{13} .

As opposed to the extraction of geometric features, an image preprocessing stage is required for the texture feature extraction to obtain aligned faces with uniform size and shape. This preprocessing task consists of the following six steps: (i) automatic facial point detection, (ii) coordinate extraction of the inner corner of the eyes, (iii) image rotation to align the eye's inner corner coordinates, (iv) image scaling proportionally to the mean distance between the eyes, (v) facial cropping using a proper bounding rectangle, and (vi) conversion of the color images to grayscale.

Census transform (CT)²⁴ is a nonparametric local transform originally developed for determining correspondences between local patches. This transform compares the intensity value of a pixel with its eight neighboring pixels, such that if its value is higher than or equal to one of its neighbors, a bit 0 is set in the corresponding location or, otherwise, a bit 1 is set. The process of CT encoding for one pixel can be illustrated in the following equation:

$$\begin{array}{cccccc} 95 & 27 & 98 & 1 & 0 & 1 \\ 40 & 69 & 82 & \Rightarrow & 0 & \times & 1 \Rightarrow 10111000 = (184)_{10}. \\ 30 & 55 & 79 & 0 & 0 & 1 \end{array} \quad (1)$$

The concatenation of the eight bits produced after the intensity comparison is then converted to a decimal number in the $[0,255]$ interval. It has been demonstrated that CT is robust to illumination changes.²⁵

The census transform histogram (CENTRIST)²⁶ is a histogram constructed from the CT values from an image, which has been successfully applied as a visual descriptor to several image classification problems.^{27,28} CENTRIST is able to describe local structures of the image, providing a high generalization for categorization and suppressing detailed textural information.

In our methodology, CENTRIST is applied to each entire image, generating a feature vector of length 256. This vector is normalized by dividing each intensity level r by the total pixels n of the image, that is

$$p(r) = \frac{h(r)}{n}, \quad (2)$$

where $h(r)$ denotes the occurrence frequency of each intensity level in the image, whereas $p(r)$ represents the probability of occurrence intensity.

3.3 Feature Reduction

Two techniques for feature reduction,²⁹ principal component analysis (PCA)³⁰ and linear discriminant analysis (LDA),³¹ are employed to maintain the most representative features, avoiding redundant or noisy information.³² These approaches are used sequentially and applied individually for each feature set.

PCA is a known technique³⁰ used to transform the original data into a lower dimensional feature descriptor. New orthogonal bases are obtained by solving the eigenvalue problem through training samples. These orthogonal bases, called eigenfaces, are suitable for image reconstruction.³³

LDA is used to search for a combination of features that discriminate class samples.³¹ The method projects the images onto a subspace that minimizes the within-class scatter and maximizes the between-class scatter of the projected data.

The combination of PCA and LDA takes advantages of both techniques, that is, data dimensionality reduction by projecting

the data onto the eigenface space followed by LDA to perform class separability.

3.4 Classification

Two different classifiers³⁴ are evaluated in our experiments, SVM and *K*-NN. The classifiers are applied to the feature vector, after its dimensionality reduction, to provide a comparison between the achieved recognition rates.

Our methodology is validated through a *k*-fold cross-validation protocol, that is, the original set of samples is randomly partitioned into *k* equal sized subsets. A single subset of samples is then kept as the validation data for testing the model, whereas the remaining *k* – 1 subsets are used as training data. The process of cross validation is repeated *k* times, such that each of the *k* subsets of samples is used exactly once as the validation data. Finally, the *k* results from the folds are averaged to generate a single estimation.

A grid search strategy is applied to look for combinations of parameter values and then select the parameters that provide the most accurate classification model.

4 Experimental Results

Our method used the dataset collected by Ferry et al.,⁹ which is composed of 199 images from publicly available or scientifically published photographs of patients diagnosed with Down syndrome. This dataset contains a collection of images of patients from different ethnicities, genders, and ages. The images were captured spontaneously from different backgrounds, angles, and distances, showing varying head poses, facial expressions, and occlusions.

We selected only images of children, discarding images of adults and at very poor resolution. The latter decision is because it precludes accurate facial fiducial point detection. The resulting image set consisted of 153 images.

We used the Dartmouth Database of Children's Faces³⁵ for obtaining images of healthy children. This dataset contains 40 male and 40 female children between 6 and 16 years of age, who posed eight facial expressions (neutral, contempt, happiness, surprise, anger, sadness, disgust, and fear). Models were photographed from various angles and under different lighting conditions. We selected a set of 153 images from the Dartmouth Database of Children's Faces,³⁵ considering males and females showing very distinct facial expressions.

Therefore, our dataset is composed of 153 images of each of the above-mentioned datasets, that is, 306 images in total to test and verify our proposed method. Then, we conducted experiments using our geometric representation, CENTRIST descriptor, and the fusion of both features through four approaches: PCA + *K*-NN, PCA + LDA + *K*-NN, PCA + SVM, and PCA + LDA + SVM.

Our methodology was validated through a 10-fold cross-validation protocol. The results are reported in Table 2, whose values represent the average detection accuracy rate obtained in the performed experiments.

From our experiments, we can observe that the geometric features are capable of reaching high-accuracy rates for Down syndrome detection. We can also notice that the PCA + LDA approach achieves higher detection rates. Furthermore, the CENTRIST descriptor provides a competitive performance with more than 90% accuracy.

Although the fusion of the geometric and texture features provides high accuracy, its result is not superior to the accuracy

Table 2 Average accuracy, in percentage, using our geometric representation and the CENTRIST descriptor on the evaluated dataset.

Recognition method	Geometric (%)	CENTRIST (%)	Geometric + CENTRIST (%)
PCA + <i>K</i> -NN	91.13	90.33	96.78
PCA + LDA + <i>K</i> -NN	95.17	94.35	97.59
PCA + SVM	95.17	93.55	97.59
PCA + LDA + SVM	98.39	95.17	98.39

The best average accuracy results are shown in bold faces.

rate obtained with only geometric features. Geometric features seem to have predominance over textural features.

Table 3 shows the best detection accuracy rates achieved with the geometric features proposed in our approach and in the method developed by Zhao et al.¹⁸ For our method, the best parameters $\gamma = 1.0$ and $C = 1$ of the radial basis function kernel SVM were obtained through a grid search to improve the classification accuracy rates. The area under the receiver operating characteristic curve (AUC) was 0.9839. For the method by Zhao et al.,¹⁸ the best parameters obtained with our implementation were achieved with $\gamma = 0.05555556$ and $C = 1$, generating an AUC = 0.9273. It is worth mentioning that the original work developed by Zhao et al.¹⁸ was evaluated in a private dataset. They achieved an average accuracy rate of 95.80% with the geometric features, 77.10% with textural features, and 97.90% with combined features.

Table 4 shows the confusion matrix obtained with the proposed method, that is, the geometric descriptor composed of 14 geometric distances combined with the PCA + LDA + SVM strategy. Table 5 shows the confusion matrix obtained with the method developed by Zhao et al.,¹⁸ that is, the geometric descriptor composed of 19 geometric distances combined with the SVM classifier.

The Wilcoxon rank-sum test³⁶ was performed to compare the results obtained between the proposed method and the approach

Table 3 Comparison of average accuracy rates (%) for Down syndrome detection over our formed dataset.

Recognition method	Strategy	Accuracy (%)
Our method	14 Geometric distances + PCA + LDA + SVM	98.39
Zhao et al. ¹⁸	19 Geometric distances + SVM	92.73

The best average accuracy results are shown in bold faces.

Table 4 Confusion matrix for the proposed method.

		Actual classes	
		Down	Healthy
Predicted classes	Down	60	2
	Healthy	0	62

Table 5 Confusion matrix for the method developed by Zhao et al.¹⁸

		Actual classes	
		Down	Healthy
Predicted classes	Down	58	4
	Healthy	5	57

developed by Zhao et al.¹⁸ This nonparametric statistical test,³⁷ which does not require the assumption of normal distributions, determined that there were significant differences between the methods (p -value = 0.000157, that is, <0.05).

There are still few works related to Down syndrome detection available in the literature. Most of these approaches are evaluated on unavailable datasets and consider <50 images for each class. These datasets use frontal faces well-positioned images without the presence of any occlusion, which is captured under constrained conditions.

It is worth mentioning that, due to the impossibility of having access to the datasets used in other methods and to perform a fair comparison, we implemented the geometric-based approach that presents the highest accuracy in the literature.¹⁸

Our method used only 16 facial fiducial points to calculate 14 distances, whereas the other approach employed 19 fiducial points, resulting in 19 geometric distances. Additionally, our method was able to perform Down syndrome detection using images captured under uncontrolled conditions, while the other approach worked with frontal images.

From the experimental results, it is possible to state that our geometric descriptor demonstrated to be very discriminative for computing a set of measurements over the facial points and capturing dysmorphic facial features present in individuals affected by Down syndrome.

5 Conclusions and Future Work

A method for recognizing Down syndrome in face images was proposed and analyzed in this work, which consists of facial fiducial point detection, feature extraction, feature reduction, and classification.

A geometric descriptor was used to extract and represent a set of facial features. Different classifiers were employed in the classification process to generate the final results.

Experimental results have shown that a geometric representation can achieve high-accuracy rates for Down syndrome recognition in the wild. Thus, geometric features have proven to be robust and independent of gender, race, and age.

As directions for future work, we intend to analyze other sets of visual features and apply the developed system to different genetic disorders.

Disclosures

The authors do not have conflicts of interest. The authors have no relevant financial interests in the paper and no other potential conflicts of interest to disclose.

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References

1. W. Reardon and D. Donnai, "Dysmorphology demystified," *Arch. Dis. Child. Fetal Neonat. Ed.* **92**(3), F225–F229 (2007).
2. K. Doi, "Computer-aided diagnosis in medical imaging: historical review, current status and future potential," *Comput. Med. Imaging Graphics* **31**(4), 198–211 (2007).
3. Q. Li and R. M. Nishikawa, *Computer-Aided Detection and Diagnosis in Medical Imaging*, Taylor and Francis, Boca Raton, Florida (2015).
4. E. Malt et al., "Health and disease in adults with Down syndrome," *Tidsskr. Nor. Laegeforen.* **133**(3), 290–294 (2013).
5. F. Hickey, E. Hickey, and K. L. Summar, "Medical update for children with Down syndrome for the pediatrician and family practitioner," *Adv. Pediatr.* **59**(1), 137–157 (2012).
6. D. Patterson, "Molecular genetic analysis of Down syndrome," *Hum. Genet.* **126**(1), 195–214 (2009).
7. R. Faragher and B. Clarke, *Educating Learners with Down Syndrome: Research, Theory, and Practice with Children and Adolescents*, Routledge, London (2013).
8. J. Y. R. Cornejo, H. Pedrini, and F. Flórez-Revuelta, "Facial expression recognition with occlusions based on geometric representation," in *Iberoamerican Congress on Pattern Recognition*, pp. 263–270, Springer, New York (2015).
9. Q. Ferry et al., "Diagnostically relevant facial gestalt information from ordinary photos," *eLife* **3**, e02020 (2014).
10. D. Landry, D. Raiside, and J. Vanhoutte, "On the classification of congenital abnormalities from hand radiographs," *Pattern Recognit.* **11**(4), 289–296 (1979).
11. H. S. Loos et al., "Computer-based recognition of dysmorphic faces," *Eur. J. Hum. Genet.* **11**(8), 555–560 (2003).
12. S. Boehringer et al., "Syndrome identification based on 2D analysis software," *Eur. J. Hum. Genet.* **14**(10), 1082–1089 (2006).
13. O. Erogul et al., "Recognition of Down syndromes using image analysis," in *14th National Biomedical Engineering Meeting*, pp. 1–4, IEEE (2009).
14. Q. Zhao et al., "Hierarchical constrained local model using ICA and its application to Down syndrome detection," in *Int. Conf. on Medical Image Computing and Computer-Assisted Intervention*, pp. 222–229, Springer, New York (2013).
15. K. Burçin and N. V. Vasif, "Down syndrome recognition using local binary patterns and statistical evaluation of the system," *Expert Syst. Appl.* **38**(7), 8690–8695 (2011).
16. S. Saraydemir et al., "Down syndrome diagnosis based on Gabor wavelet transform," *J. Med. Syst.* **36**(5), 3205–3213 (2012).
17. A. David and B. Lerner, "Support vector machine-based image classification for genetic syndrome diagnosis," *Pattern Recognit. Lett.* **26**(8), 1029–1038 (2005).
18. Q. Zhao et al., "Down syndrome detection from facial photographs using machine learning techniques," *Proc. SPIE* **8670**, 867003 (2013).
19. P. Kruszka et al., "Down syndrome in diverse populations," *Am. J. Med. Genet. Part A* **173**(1), 42–53 (2017).
20. P. Viola and M. J. Jones, "Robust real-time face detection," *Int. J. Comput. Vision* **57**(2), 137–154 (2004).
21. D. E. King, "Dlib-ml: a machine learning toolkit," *J. Mach. Learn. Res.* **10**, 1755–1758 (2009).
22. A. L. Creavin and R. D. Brown, "Ophthalmic abnormalities in children with Down syndrome," *J. Pediatr. Ophthalmol. Strabismus* **46**(2), 76–82 (2009).
23. C. J. Epstein et al., "Protocols to establish genotype-phenotype correlations in Down syndrome," *Am. J. Hum. Genet.* **49**(1), 207–235 (1991).
24. R. Zabih and J. Woodfill, "Non-parametric local transforms for computing visual correspondence," in *European Conf. on Computer Vision*, pp. 151–158, Springer, New York (1994).
25. R. Ranftl et al., "Pushing the limits of stereo using variational stereo estimation," in *IEEE Intelligent Vehicles Symp.*, pp. 401–407, IEEE (2012).
26. J. Wu and J. M. Rehg, "CENTRIST: a visual descriptor for scene categorization," *IEEE Trans. Pattern Anal. Mach. Intell.* **33**(8), 1489–1501 (2011).
27. J. Cornejo and H. Pedrini, "Automatic fruit and vegetable recognition based on CENTRIST and color representation," *Lect. Notes Comput. Sci.* **10125**, 76–83 (2016).

28. J. Cornejo and H. Pedrini, "Recognition of occluded facial expressions based on CENTRIST features," in *IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, Shanghai, pp. 1298–1302 (2016).
29. L. Cao et al., "A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine," *Neurocomputing* **55**(1–2), 321–336 (2003).
30. I. T. Jolliffe, *Principal Component Analysis*, Springer-Verlag, New York (2002).
31. R. A. Fisher, "The use of multiple measurements in taxonomic problems," *Ann. Eugen.* **7**(2), 179–188 (1936).
32. A. M. Martinez and A. C. Kak, "PCA versus LDA," *IEEE Trans. Pattern Anal. Mach. Intell.* **23**(2), 228–233 (2001).
33. M. S. Park, J. H. Na, and J. Y. Choi, "PCA-based feature extraction using class information," in *IEEE Int. Conf. on Systems, Man and Cybernetics*, Vol. 1, pp. 341–345, IEEE (2005).
34. K. Fukunaga, *Introduction to Statistical Pattern Recognition*, Academic Press, New York (2013).
35. K. A. Dalrymple, J. Gomez, and B. Duchaine, "The Dartmouth database of children's faces: acquisition and validation of a new face stimulus set," *PLoS One* **8**(11), e79131 (2013).
36. H. B. Mann and D. R. Whitney, "On a test of whether one of two random variables is stochastically larger than the other," *Ann. Math. Stat.* **18**, 50–60 (1947).
37. G. W. Corder and D. I. Foreman, *Nonparametric Statistics: A Step-by-Step Approach*, John Wiley and Sons, Hoboken, New Jersey (2014).

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