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Stochastic Fuzzy Modeling for Ear Imaging Base Child Identification

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Abstract

The unique identification of children is crucial for information technology supported vaccine delivery to the unprivileged population of third world countries. New robust image matching algorithms are required to match two ear photographs taken under nonstandard real-world conditions such as the presence of unwanted background objects in the photographs. This paper applies stochastic fuzzy models to the robust matching of ear images. The local features of the image regions are extracted using a "force-field-like" transformation. The extracted features of an image region are modeled by a stochastic fuzzy system. A region of an image is matched to a region of another image by matching the features of an image's region with the model of another image's region. As the model is fuzzy as well as stochastic, a robust matching of features' data to a model is facilitated by handling any uncertainties arising from fuzziness and randomness of the image features. The study introduces an information-theoretic index for measuring the degree of matching between image features and a model of the features. Several experiments are performed on a database of 750 ear-photographs of children (0–6 years) to justify the novel stochastic fuzzy image matching method.

Keywords: Features, fuzzy models, image matching, robustness,Student-t distribution, variational Bayes.
Reviewed by* **ICETSET'16 *organizing committee*

1. Introduction

Immunization is the most cost effective medical intervention to reduce the morality rates for infants and children under five. We are developing a concept of mobile phone based child identification for improved immunization in developing countries under a collaborative project between the" Center for Life Science Automation, Rostock, Germany,"

"Shah Satnamji Green-S Welfare Force Wing, Sirsa, India."The child's ear photograph taken by a mobile phone must be matched with in-database existing ear photographs for an accurate identification of small children and infants. This is of significance in information technology supported health care delivery to the underprivileged

population of developing countries where a reliable mechanism for the identification and registration of the masses is not in place. The problem of ear imaging based child identification is challenging due to the changes in the photographic conditions (such as illumination distance of camera, viewpoint, background, and so on) and the presence of unwanted objects in the background of the photograph. Therefore, a robust matching of photographs is required. Matching of similar structures between digital images is a fundamental step in computer vision and image processing applications. There is always an interest in comparing theobjects' shape between two images. A shape descriptor that captures the distribution of the points relative to a referencepoint was proposed in **[1].** Hausdorff distance is a widely usedmathematical construct for measuring the distance betweentwo edge maps (i.e., point datasets) and this distance can becalculated without requiring any correspondence between thepoints **[2].** Mahalanobis distance is another metric applied forimage processing applications **[3].** The state-of-the-art algorithmstypically identify the regions of interest in images, associate scale/rotation invariant descriptors to eachregion, and finally descriptors are matched to establish correspondencesbetween the images' regions. This is referredto as local features based matching of images. The milestonework **[4]** introduced a scale-invariant feature transform (SIFT) that first uses difference-of-Gaussian region detector and thencalculates descriptors based on the gradient orientation distributionin the region. The local features can be matchedby defining a suitable dissimilarity measure between featuresand a matching criterion **[5].** Also, the local features can be used with the machine learning methods for object classification**[6].** The SIFT methods are the best known techniques forimage matching applications as these methods are invariantto image scaling and rotation and partially invariant to illuminationand viewpoint changes. The SIFT method has beenextended to a fully affine invariant image matching framework**[7].** It is natural that fuzzy researchers are motivatedto exploit the uncertainty handling potential of fuzzy systemsin robust image matching. Biswas*et al.* **[8]** have proposedthe comparing of fuzzy membership-distance products, calledmoment descriptors, for image matching. Also, the fuzzy transformof an image can be compared with the fuzzy transform ofanother image to measure the grade of similarity between twoimages **[9].** Kumar *et al.* [**13]–[15]** have recently introduced the stochasticfuzzy models that potentially may serve as a useful signalanalysis tool in the presence of uncertainties. The main motivationof this paper is to validate the hypothesis that themathematical theory of stochastic fuzzy models is capableof handling any of the image features. The salient features of thestochastic fuzzy approach to image matching are as follows.The image is processed by a transformation similar (but notidentical) to the force field [16]. The transformation reinforcesthe edges and extracts the image features. A finite number ofsub-images are created by the fuzzy *c*-means clustering ofthe position coordinates of stronger edges. A fuzzy clustering based Takagi–Sugeno fuzzymodel is meant for the modeling of the image features. Itis assumed that the image features are contaminated withthe noises. The parameters of the stochastic fuzzy modelare inferred under variational Bayes framework **[17]–[21]**and robustness is achieved by modeling the noises with theStudent-t distributions **[22], [23].** This paper introduces aninformation-theoretic index for measuring the degree of matchingbetween image features and a model of the features.The matching score between data and a model is

defined asthe average value of log-likelihood when parameters of thestochastic model are drawn from those variational distributionsthat maximize a lower bound on mutual information.Each subimage of an image is matched with all of the subimagesof other image. The pair of sub-images with the highest matching scores corresponds to the "similar" regions in thetwo images.The literature on image processing algorithms is vast. However, uncertainty handling capabilities of fuzzy modelshave not been exploited till now to find out the similar regionsin the two images under the wide range of photographic conditions.To the authors' best knowledge, this is the first studyto apply stochastic fuzzy models for robust matching of theobjects appearing in different images. The methodology hasbeen developed for the ear imaging based unique identificationof infants and young children in information technology supported health care delivery to the unprivileged population of third world countries. The novelties and original contributionsof this paper are as follows.

1) The idea of identifying infants and children via ear imaging for information technology supported vaccine delivery in developing countries is novel.

2) The modeling of the image features through a stochasticfuzzy system with Student-t distributed inputs/outputnoises and using an information-theoretic matchingdegree, instead of directly matching the image features,are the novelties of this paper.

3) The study introduces and derives analytically in Section IV the matching score between data and

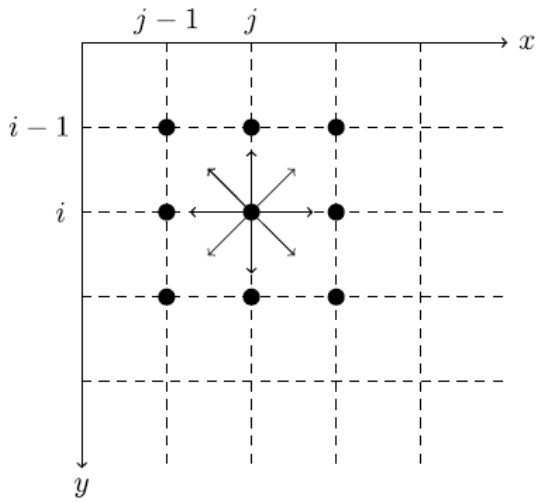


Fig. 1. Force experienced by a pixel due to the immediate neighboring pixels is calculated by using principle-of-superposition.

a model. The matching score is defined as theaverage value of log-likelihood when parameters ofthe stochastic model are drawn from those variational distributions that maximize a lower bound on mutual information.

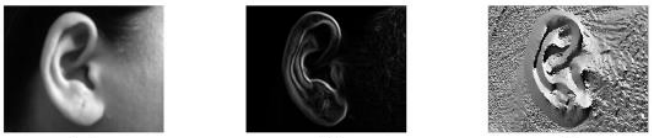
4) A database of 750 ear photographs of children (0–6 years) built by taking photographs through a mobile phone under the field conditions of immunization has been studied in Section VI. The study validates the followingargument: "while a direct matching of the imagefeatures is not sufficient to achieve robustness againstreal-world photographic conditions, the application ofstochastic fuzzy theory together with an

informationtheoreticsimilarity measure is an effective approach forrobust matching of image regions. Thus, the proposedmethod was observed performing better than the benchmarkimage matching methods of histograms of orientedgradients (HOGs) **[24],** SIFT**[4],** speeded-up robustfeatures (SURFs) **[25],** and affine-SIFT (ASIFT) **[7]** in matching the ear-geometries between the two photographswhich have been taken under field conditions."

2.Image Features Extraction

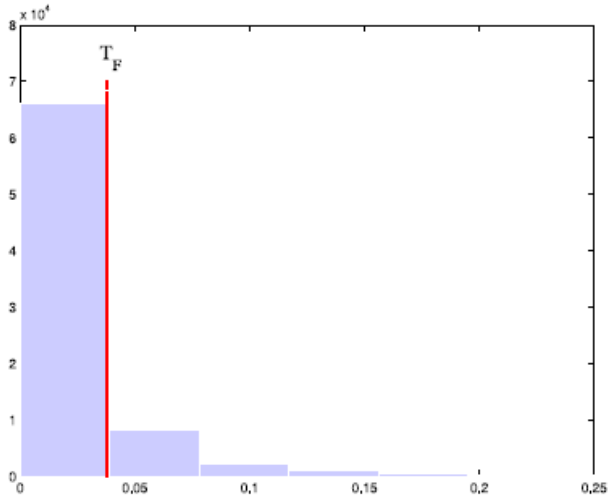
In the context of ear biometrics, Hurley *et al.* [**16]** haveintroduced a force field transformation where the image istreated as an array of Gaussian attractors that act as thesource of a force field. We introduce here similar to the studyof **[16]** another force-field-like transformation. With referenceto Fig. 1, it is assumed that each pixel of the image attractsall of its eight neighboring pixels toward itself with a forcesuch that the magnitude of force is directly proportional to theproduct of intensities of the two pixels and is inversely proportionalto the square of the distance between the two pixels.

$$\vec{F}_{ij} = \sum_{i',j'} \frac{I(i,j)I(i',j')}{\|\vec{p}(i',j') - \vec{p}(i,j)\|^3} (\vec{p}(i',j') - \vec{p}(i,j))$$



(a) (b) (c)

Fig. 2.Force-field like transformation of an ear image assuming a neighborhood of eight pixels. (a) Ear photograph. (b) Magnitude of force. (c) Direction of force.



. Fig. 3. Example of the histogram of force magnitude values for an image.

First, a pixel experiences forces only from its eight immediateneighboring pixels and not from all of the image pixels.Second, the transformation of [**16],** unlike here introducedtransformation, assumes a unit intensity of the pixel at whichforce due to otherpixels is calculated. As force is a vectorquantity, it ispossible to calculate magnitude and direction.

Remark 1: The choice of threshold value on force magnitude,proposed by (1), is derived from the experimentalobservations regarding the histogram of force magnitude values.Fig. 3 provides an example of the histogram of forcemagnitude values for an image. The threshold value, calculatedby (1), is marked in Fig. 3. It can be observed fromFig. 3 that the proposed choice of threshold value clearlyseparates the edge-pixels from the pixels with a lower force magnitude.All the edge-pixels that are connected to at least one non edge pixel are referred to as boundary-pixels and havebeen marked in Fig. 4(a) as white dots. Once the boundarypixelshave been extracted, a square-sized block, boundaringthe boundary-pixels, can be drawn on the image. Fig. 4(a) alsodisplays the boundary-block and its center. The positioncoordinatesof boundary-pixels can be divided into a finitenumber of clusters using e.g., fuzzy *c*-means clustering.Further, a boundary-block could be drawn around the pixels ofeach cluster giving rise to a finite number of boundary-blocks.Fig. 4(b)–(d) displays the boundary-blocks for 2, 4, and 8 clusters,respectively. Please note that the overlapping betweenboundary-blocks exists as each boundary-block is forced tobe of square-sized.The boundary-block is a subimage and one can extractwithin the block lying boundary-pixels bythresholding theforce-magnitude as described previously, however, mean andvariance are calculated locally of the pixels lying with the block.

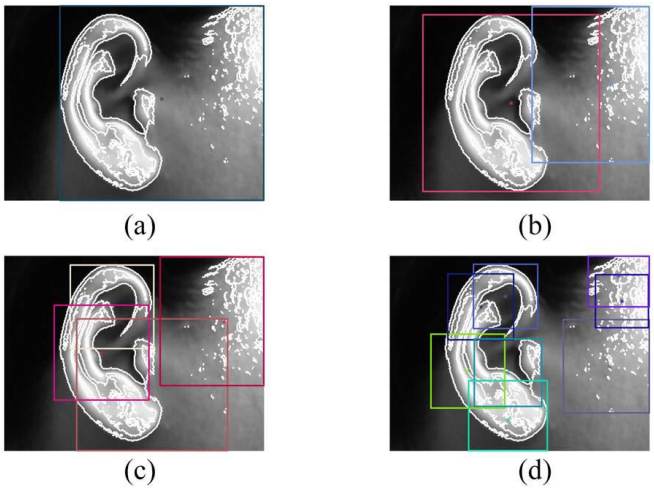


Fig. 4.Extraction of the boundary-pixels and their clustering. (a) Boundarypixels.(b) Number of clusters = 2. (c) Number of clusters = 4. (d) Numberof clusters = 8.

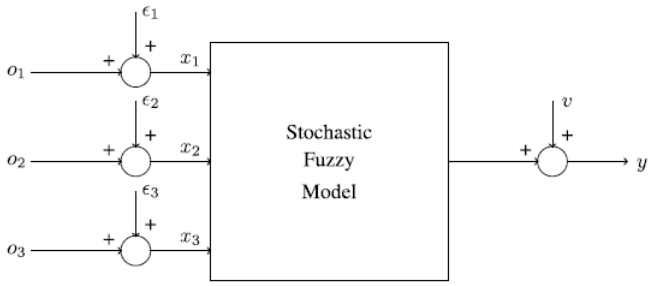


Fig. 5. Stochastic fuzzy modeling of image features.

3.Stochastic Fuzzy Modeling Of Image Features

It is assumed that the parameters *(x*1, *x*2, *x*3, *y)*, definedby (2)–(5), are being affected by the additive disturbances*(*_1, _2, _3, *v)*, respectively, and a stochastic fuzzy model identifiesthe relationship between input variables *(x*1, *x*2, *x*3*)* andthe output variable *y*. This modeling of image features is illustratedby Fig. 5. A fuzzy clustering based Takagi–Sugenofuzzy model, described in Appendix A, was considered forthe modeling of the image features. The model described inFig. 5 is a three-inputs-single-output system. However, we formulate the modeling problem mathematically for a general *n*−inputs-single-output system.

Algorithm 1 Data Modeling Algorithm (as in [21])

Require: Inputs-output data pairs $\{x(k), y(k)\}_{k=1}^{N}$ and vectors $\{G(x(k))\}_{k=1}^{N}$ defined by the fuzzy model.

1: Choose initially the parameters of prior distributions as $\Lambda_o = I$, $\mu_o = 0$, $a_{x,\lambda} = b_{x,\lambda} = 10^{-3}$, $a_{x,d} = b_{x,d} = 10^{-3}$, $\Lambda_\alpha = I$, $a_{y,\lambda} = b_{y,\lambda} = 10^{-3}$, $a_{y,d} = b_{y,d} = 10^{-3}$.

2: **while** $(k = 1, 2, \ldots, N)$ **do**

3: Initialize the parameters of variational distributions as $\hat{\Lambda}_o = \Lambda_o$, $\hat{\mu}_o = \mu_o$, $\hat{a}_{x,\lambda} = a_{x,\lambda}$, $\hat{b}_{x,\lambda} = b_{x,\lambda}$, $\hat{a}_{x_j,z} = \hat{b}_{x_j,z} = 10^{-3}$, $\hat{a}_{x,d} = a_{x,d}$, $\hat{b}_{x,d} = b_{x,d}$, $\hat{\Lambda}_\alpha = \Lambda_\alpha$, $\hat{\mu}_\alpha = \mu_\alpha$, $\hat{a}_{y,\lambda} = a_{y,\lambda}$, $\hat{b}_{y,\lambda} = b_{y,\lambda}$, $\hat{a}_{y,z} = \hat{b}_{y,z} = 10^{-3}$, $\hat{a}_{y,d} = a_{y,d}$, $\hat{b}_{y,d} = b_{y,d}$.

4: Update all the parameters of variational distributions with the data pair $(x(k), y(k))$ as per the equations listed in Result 1.

5: The parameters updated with $k-$th data pair become prior for $(k+1)-$th data pair, i.e., $\Lambda_o = \hat{\Lambda}_o$, $\mu_o = \hat{\mu}_o$, $a_{x,\lambda} = \hat{a}_{x,\lambda}$, $b_{x,\lambda} = \hat{b}_{x,\lambda}$, $a_{x,d} = \hat{a}_{x,d}$, $b_{x,d} = \hat{b}_{x,d}$, $\Lambda_\alpha = \hat{\Lambda}_\alpha$, $\mu_\alpha = \hat{\mu}_\alpha$, $a_{y,\lambda} = \hat{a}_{y,\lambda}$, $b_{y,\lambda} = \hat{b}_{y,\lambda}$, $a_{y,d} = \hat{a}_{y,d}$, $b_{y,d} = \hat{b}_{y,d}$.

6: $k \leftarrow k + 1$.

7: **end while**

8: **return** the parameters of variational distributions: $(\hat{\mu}_o, \hat{\Lambda}_o)$, $(\hat{a}_{x,\lambda}, \hat{b}_{x,\lambda})$, $(\hat{a}_{x,d}, \hat{b}_{x,d})$, $(\hat{\mu}_\alpha, \hat{\Lambda}_\alpha)$, $(\hat{a}_{y,\lambda}, \hat{b}_{y,\lambda})$, $(\hat{a}_{y,d}, \hat{b}_{y,d})$. The algorithm should also return the membership functions related parameters (i.e. cluster centers and variances) which are required to compute vector $G(\cdot)$.

Algorithm 2 Data Matching Algorithm

Require: Inputs-output data pairs $\{x(k), y(k)\}_{k=1}^{N}$ to be matched; the parameters of prior distributions: (μ_o, Λ_o), $(a_{x,\lambda}, b_{x,\lambda})$, $(a_{x,d}, b_{x,d})$, $(\mu_\alpha, \Lambda_\alpha)$, $(a_{y,\lambda}, b_{y,\lambda})$, $(a_{y,d}, b_{y,d})$; and the membership functions related parameters required to compute vectors $\{G(x(k))\}_{k=1}^{N}$. Please note that the parameters of prior distributions and of membership functions completely characterize a model and have been returned (i.e., estimated) by running Algorithm 1 on some other dataset.

1: Initialize the parameters of variational distributions as $\hat{\Lambda}_o = \Lambda_o$, $\hat{\mu}_o = \mu_o$, $\hat{a}_{x,\lambda} = a_{x,\lambda}$, $\hat{b}_{x,\lambda} = b_{x,\lambda}$, $\hat{a}_{x_j,z} = \hat{b}_{x_j,z} = 10^{-3}$, $\hat{a}_{x,d} = a_{x,d}$, $\hat{b}_{x,d} = b_{x,d}$, $\hat{\Lambda}_\alpha = \Lambda_\alpha$, $\hat{\mu}_\alpha = \mu_\alpha$, $\hat{a}_{y,\lambda} = a_{y,\lambda}$, $\hat{b}_{y,\lambda} = b_{y,\lambda}$, $\hat{a}_{y,z} = \hat{b}_{y,z} = 10^{-3}$, $\hat{a}_{y,d} = a_{y,d}$, $\hat{b}_{y,d} = b_{y,d}$.

2: Update all the parameters of variational distributions with the data pairs $\{x(k), y(k)\}_{k=1}^{N}$ as per the equations listed in Result 2 where expectations over $p(x, y)$ are calculated by using sample averages.

3: Apply Result 3 on data pairs $\{x(k), y(k)\}_{k=1}^{N}$ with the updated parameters of variational distributions to calculate MS. Again, the expectations over $p(x, y)$ are calculated by using sample averages.

4: **return** Matching score MS.

Taking expectation over $p(x, y)$, we have

$$\left\langle \int \partial\Omega\, q^*(\Omega) \log(p(x, y|\Omega)) \right\rangle_{p(x,y)}$$
$$= -\frac{n+1}{2} \log(2\text{pi}) + \frac{n}{2} \langle \log(\lambda_x) \rangle_{q^*(\lambda_x)}$$
$$+ \frac{1}{2} \sum_{j=1}^{n} \langle \log(z_{x_j}) \rangle_{q^*(z_{x_j})} - \frac{1}{2} \langle \lambda_x \rangle_{q^*(\lambda_x)}$$
$$\times \left\langle \left\langle (x-o)^T \begin{bmatrix} \langle z_{x_1} \rangle_{q^*(z_{x_1})} & & \\ & \ddots & \\ & & \langle z_{x_n} \rangle_{q^*(z_{x_n})} \end{bmatrix} (x-o) \right\rangle_{q^*(o)} \right\rangle_{p(x)}$$
$$+ \frac{1}{2} \langle \log(\lambda_y) \rangle_{q^*(\lambda_y)} + \frac{1}{2} \langle \log(z_y) \rangle_{q^*(z_y)}$$
$$- \frac{1}{2} \langle \lambda_y \rangle_{q^*(\lambda_y)} \langle z_y \rangle_{q^*(z_y)} \left\langle \left\langle \left| y - (G(x))^T \alpha \right|^2 \right\rangle_{q^*(\alpha)} \right\rangle_{p(x,y)}.$$

4.Image Matching Algorithm

Finally, all of the theoretical results presented in this paperare carefully put together to develop an image matchingalgorithm (Algorithm 3) for finding the similar regions in twoimages and giving an overall matching degree between the two images. The functionality of Algorithm 3 is as follows.

1) First of all, *Ka*sub-images of image *Ia*and *Kb* subimagesof image *Ib*are created.

2) The image features associated to each boundary-blockare modeled by Algorithm 1 provided that the boundaryblockhas at least 500 data points. The reason for setting the requirement of 500 data points is that the inferredstochastic fuzzy model might not be sufficiently accurateif the number of data points is not sufficiently large. Aninaccurate model leads to dubious matching results.

3) Each subimage (referred to as boundary-block) of animage is matched with all of the sub-images of otherimage at steps 11 and 12.

4) The *i*thsubimage of image *Ia*is considered matched tothe *j*∗thsubimage of image *Ib*, if:

a) *i*thsubimage of image *Ia*matches highest to *j*∗th subimage of image *Ib*;

b) *j*∗thsubimage of image *Ib*matches highest to *i*th

subimage of image *Ia*.

5) The pairs of matching sub-images correspond to the similar regions in the two images.

6) Each pair of matching sub-images contributes to the overall matching degree between the images at step 18.The algorithms were implemented using MATLAB R2014a.The computational time required by Algorithm 3 dependsupon the number ofboundary-blocks processed by the algorithmand the number of boundary-pixels associated to each boundary-block. Algorithm 3 hardly makes computations butinvokes multiple times the Algorithm 1 for modeling andAlgorithm 2 for matching. It was observed that for a subimage with*N* boundary-pixels, a nonoptimized MATLAB code on aMacBook Pro machine with a 2.9-GHz Intel Core i7 processorresults in the modeling time in milli-seconds $\approx 1.95 \times N$ the matching time in milli-seconds $\approx 0.45 \times N$.

5.Ear Imaging For Child Identification

The considered application example is concerned with the unique identification of infants and young children forinformation technology supported vaccine delivery to theunprivileged population of third world countries. We haveproposed a mobile phone based identification and vaccinationinformation management system that addresses the global health problem of no or incomplete vaccination of children byeffectively reaching the children through community workers,identifying the mother–child unit, educating the people aboutimmunization programs, and electronically documenting the immunization events. The integrated camera of the mobilephone is used to take the child's ear photograph. A mobileapplication facilitates the comparison of child's ear photographwithin the server's database existing candidate photographs tofind the most matching ear photograph. The identity of thechild is verified by the community health worker dependingupon if the personal details of the child of query photographmatch with the personal details of the child of most matchingphotograph. Our approach is to use the benchmark SIFTmethod to quickly scan the database for generating the candidatephotographs. Algorithm 3 can be run on relatively smallnumber of candidate photographs for robust matching. Theapplication, due to a relatively small number of candidatephotographs, does not pose a challenge in terms of the computationtime of the image matching algorithm but in terms ofthe robustness. A robust image matching algorithm, capable ofperforming identification under real-world photographic conditions(such as the presence of unwanted background objectsin the photographs), is demanded. Furthermore, the algorithmis desired to be robust toward factors such as illumination,distance of camera, and viewpoint.To demonstrate the effectiveness of the Algorithm 3 inrobust matching of ear images, a database of 750 ear photographsof children (0–6 years) is studied. The database mightinclude up to five different ear photographs of the same child which have been taken at different points of time under different photographic conditions. Fig. 6 displays a few samplesfrom the database which act as the query photographs todemonstrate the application potential of the proposed method.The ground truth of each query photograph is another photographof the ear of the same child in the database. For a givenquery photograph, the candidate photographs are generated bya quick scan of database by SIFT method as follows.

1) All the photographs of database are ranked as per theirnumber of SIFT key-point matches.

2) The photographs, achieving a rank (as per the SIFTmethod) higher than or equal to the rank of a child's earphotograph with the same name and date-of-birth as thename and date-of-birth of the child of query photograph,serve as the candidate photographs for Algorithm 3 andother considered image matching methods.

Remark 3: As ear images are differently scaled, a simplecorrelation between the images cannot be used to generate thecandidate photographs. Therefore, SIFT, being scale invariant,was used to generate the candidate photographs. It is observed for SIFT that despite some wrong key-point matches, thenumber of matching key-points between two images increasesconsiderably in the case of a common object between two photographs.Thus, photographs have been ranked as per numberofSIFT key-point matches. Fig. 7 displays the most matchingphotographs to the query photographs found by SIFT. Asobserved from Fig. 7, the key-points lying on backgroundregions affect adversely and thus lead to the incorrect matchingof ear photographs. Therefore, a method robust to real-worldphotographic conditions is required.To directly match the image features without applyingstochastic fuzzy theory, the following methodologies areconsidered.

1) HOGs features [24] encode local shape information fromregions within an image and thus the inverse squaredEuclidean distance between the HOG features of twoimages is a measure of the similarity between twoimages.

2) The number of key-point matches between two imagesfound by widely used SIFT method is a measure of thesimilarity between two images.

3) Similarly to SIFT, the SURFs [25] is another image matching method defining the descriptor based on the spatial distribution of first-order Haar wavelet responsesin the x- and y-direction. The SURF could be morerobust against different image transformations thanSIFT. The number of key-point matches between twoimages found by SURF method is a measure of thesimilarity between two images.

4) ASIFT [7] is a fully affine invariant image comparisonmethod that allows to reliably identify image featuresunder very large affine distortions. The number of keypointmatches between two imagesfound by ASIFTmethod is a measure of the similarity between twoimages.

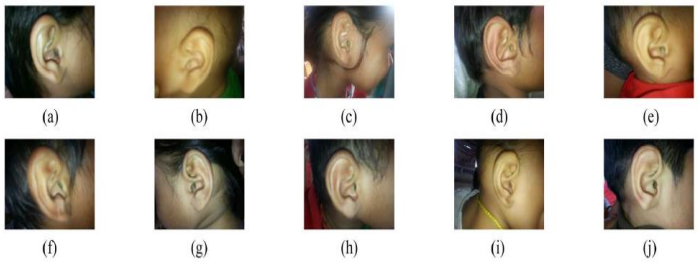


Fig. 6. Few samples from the database of children's ear photographs. (a) Query photograph 1. (b) Query photograph 2. (c) Query photograph 3. (d)Query photograph 4. (e) Query photograph 5. (f) Query photograph 6. (g) Query photograph 7. (h) Query photograph 8. (i) Query photograph 9. (j) Queryphotograph 10.

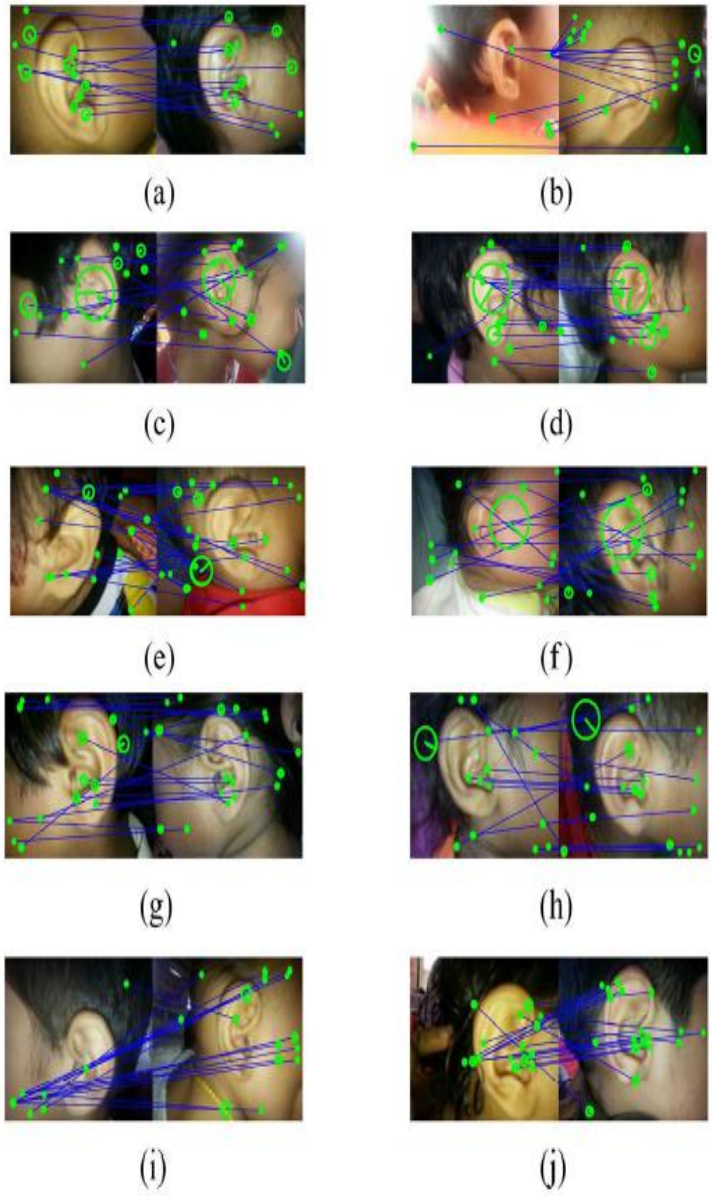


Fig. 7. Most matching photographs to the query photographs found by SIFT. (a) Query photograph 1. (b) Query photograph 2. (c) Query photograph 3. (d) Query photograph 4. (e) Query photograph 5. (f) Query photograph 6. (g) Query photograph 7. (h) Query photograph 8. (i) Query photograph 9. (j)
Query photograph 10.

TABLE I
COMPARISON OF DIFFERENT METHODS IN TERMS OF NUMBER OF CORRECTLY IDENTIFIED CHILDREN

method	correct identifications by most matching photo
Algorithm 3	10
HOG	5
SIFT	0
SURF	4
ASIFT	4

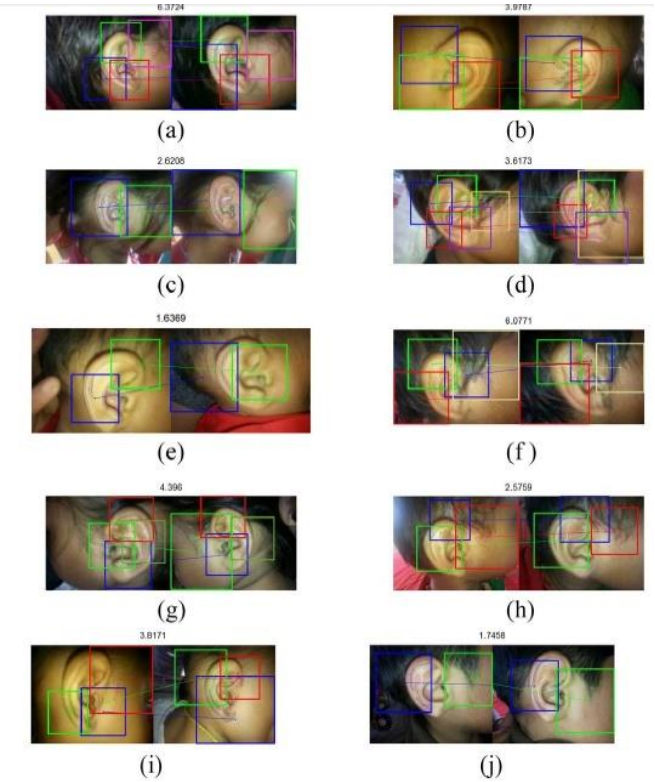


Fig. 8. Most matching photographs to the query photographs found by Algorithm 3. (a) Query photograph 1. (b) Query photograph 2. (c) Query photograph 3. (d) Query photograph 4. (e) Query photograph 5. (f) Query photograph 6. (g) Query photograph 7. (h) Query photograph 8. (i) Query photograph 9. (j) Query photograph 10.

The different methods were compared in terms of the numberof correctly identified children. Table I lists the numberof times a method could find the true match in ten differentexamples of query photographs, i.e., the number of times thebestmatching photograph to a query photograph is same as the ground truth of the query

photograph. As observed fromTable I, none of the considered methods (i.e., HOG, SIFT,SURF, and ASIFT), unlike the proposed method, could correctlyidentify the ear photograph in all of the ten examples.The found matches by Algorithm 3 have been displayed inFig. 8.To objectify theperformance of different methods, a poolof candidate photographs is created byaccumulating the candidatephotographs of all the ten query photographs. The socreated pool contained in total 152 ear photographs. For eachof the query photographs, a binary classifier was built to classify any candidate photograph from the pool either as truematch or false match. The classifier, for a given image matchingmethod, thresholds the matching score between query andcandidate photograph to classify the candidate photograph.The classification performance of different methods is compared by studying their receiver operating characteristic (ROC)curves. Fig. 9 plots the ROC curve and Table II reports thearea under ROC curve for the considered methods. The betterperformance of Algorithm 3 than HOG, SIFT, SURF, andASIFT methods is clearly observed from Fig. 9 and Table II.

The experimental results validate the argument that whilea direct matching of the image features (calculated byHOG, SIFT, SURF, and ASIFT methods) is not sufficientto achieve robustness against real-world photographic conditions,the application of stochastic fuzzy theory together with an information-theoretic similarity measure is an effectiveapproach for robust matching of image regions. Thus,the stochastic fuzzy theory offers a promising method forear imaging based identification of infants and young children under real world photographic conditions.

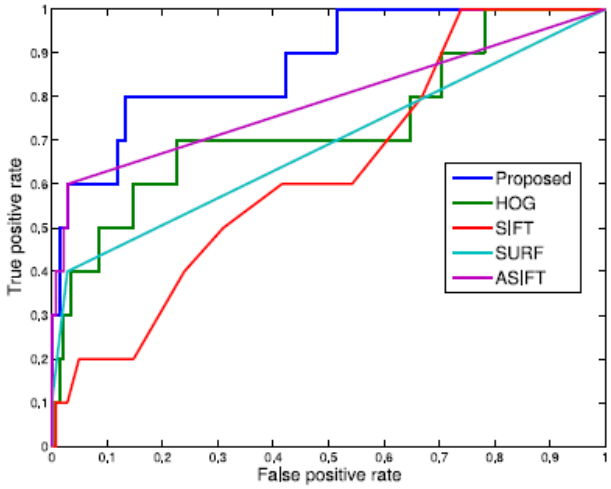


Fig. 9. ROC curves for proposed, HOG, SIFT, SURF, and ASIFT methods.

TABLE II
COMPARISON OF DIFFERENT METHODS IN TERMS OF CLASSIFICATION PERFORMANCE

method	area under ROC curve
Algorithm 3	0.875352
HOG	0.733099
SIFT	0.630986
SURF	0.687324
ASIFT	0.788732

6.Conclusion

This paper has formulated the image matching problem inthe framework of fuzzy modeling. The most important contributionof this paper is to apply the mathematical theoryof stochastic fuzzy models to define a robust matching scorebetween two images. The theoretical results are independent ofthe choice of image features and thus the proposed approachcan be used with any choice of the image features. The currentlyused image features are in their most basic forms andthus several modifications can be tried. Despite a very simple choice of image features the robustness of the image matchingalgorithm is attributed to the effectiveness of stochasticfuzzy theory in dealing with the uncertainties. Algorithm 3, arobust image matching algorithm, was observed to be effectivefor a robust matching of ear-geometries between the twophotographs which have been taken without controlled conditions.It is our future research task to extend the proposedmethod to a technique with applications to computer vision.

REFERENCES

[1] S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognitionusing shape contexts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 4, pp. 509–522, Apr. 2002.
[2] C.-H. T. Yang, S.-H. Lai, and L.-W. Chang, "Hybrid image matchingcombining Hausdorff distance with normalized gradient matching," *Pattern Recognit.*, vol. 40, no. 4, pp. 1173–1181, 2007.
[3] S. Xiang, F. Nie, and C. Zhang, "Learning a Mahalanobis distance metricfor data clustering and classification," *Pattern Recognit.*, vol. 41, no. 12,pp. 3600–3612, Dec. 2008.
[4] D. G. Lowe, "Distinctive image features from scale-invariant keypoints,"*Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Nov. 2004.
[5] J. Rabin, J. Delon, and Y. Gousseau, "A statistical approach to the matchingof local features," *SIAM J. Imag. Sci.*, vol. 2, no. 3, pp. 931–958, 2009.
[6] T. Deselaers, G. Heigold, and H. Ney, "Object classification by fusingSVMs and Gaussian mixtures," *Pattern Recognit.*, vol. 43, no. 7, pp. 2476–2484, 2010.
[7] J.-M. Morel and G. Yu, "ASIFT: A new framework for fully affine invariantimage comparison," *SIAM J. Imag. Sci.*, vol. 2, no. 2, pp. 438–469,2009.
[8] B. Biswas, A. Konar, and A. K. Mukherjee, "Image matching with fuzzymoment descriptors," *Eng. Appl. Artif. Intell.*, vol. 14, no. 1, pp. 43–49,2001.
[9] F. D. Martino and S. Sessa, "Image matching by using fuzzy transforms,"*Adv. Fuzzy Syst.*, vol. 2013, Jan. 2013, Art. ID 760704.
[10] M. Amiri and H. R. Rabiee, "A novel rotation/scale invariant templatematching algorithm using weighted adaptive lifting scheme transform,"