

INF???: Machine Learning Final Report

**Skin Segmentation**

Sasha Nicolas

Axelle Pochet

Professor: Ruy Milidiu

Pontifical Catholic University of Rio de Janeiro

Rua Marquês de São Vicente, 225, Gávea, Rio de Janeiro

State of Rio de Janeiro

22451-900

Table of contents

[1. The Dataset 4](#_Toc405905539)

[2. State of the Art 4](#_Toc405905540)

[3. Fuzzy decision tree 5](#_Toc405905541)

[3.1 General principle 5](#_Toc405905542)

[3.2 Fuzzy clustering 5](#_Toc405905543)

[3. 2.1 Fuzzy c-mean algorithm 5](#_Toc405905544)

[3.2.2 Membership functions 6](#_Toc405905545)

[3.3 Tree construction 7](#_Toc405905546)

[3.3.1 Usual decision trees 7](#_Toc405905547)

[3.2.2 Fuzzy decision trees 8](#_Toc405905548)

[3.4 Testing 11](#_Toc405905549)

[3.4.1 Rules extraction 11](#_Toc405905550)

[3.4.2 Example 12](#_Toc405905551)

[3.4.3 Testing results 12](#_Toc405905552)

[4. Application to new data 12](#_Toc405905553)

INTRODUCTION = motivations

# The Dataset

<https://archive.ics.uci.edu/ml/datasets/Skin+Segmentation>

3 Attributes B, G, R ranged from 0 to 255.

Decision class Y = 1 or 2 respectively Skin or Non-Skin

245057 instances

Not really balanced: 50859 skin against 194198 non-skin.

It was obtained from by randomly sampling face images from different age groups, skin colors and gender from FERET database (http://face.nist.gov/colorferet/request.html) and PAL database (<http://agingmind.utdallas.edu/facedb/>).

Points (R,G,B) were displayed in 3D to allow visual appraisal of the data (Figure 1).

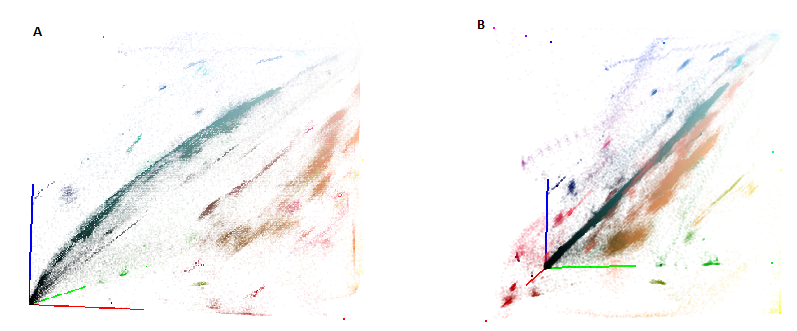


Figure : Dataset in 3D, points coordinates are (R,G,B). Colors of the axis correspond to each attributes. Points were given a transparence, allowing to see better where they form clusters. (A) and (B) Different points of view.

# State of the Art

[Bhatt et al., 2009] use a fuzzy decision tree to classify the data. The term “fuzzy” is a synonym of “blur”: here it represents the limits between different colors that are not clear, as shown in Figure 2. The Fuzzy Decision Tree takes into account the fuzziness of the data, as detailed in Part 3.1.



Figure : Colors vary smoothly, continuously. It is not possible to place exact limits between them.

[Bhatt et al., 2009] arrive at a result of 0,941 accuracy. Their confusion matrix is given below (Figure 2).

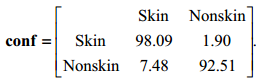


Figure : Confusion matrix from [Bhatt et al., 2009]. The main errors come from pixels asserted Skin whereas they were Non-Skin (7.48%).

# Fuzzy decision tree

## 3.1 General principle

As introduced in Part 2, fuzzy decision trees take into account the blur that may occur at the limit between classes. For example, say we have one numerical attribute *Temperature* and we want to know if a given temperature reading is *hot* or *cold*. Can we consider a temperature of 15◦C as being *hot* or *cold*? This appraisal depends on every person. Consequently, fuzzy logic allows one attribute value to belong to several classes, with a degree of certainty. The sentence “15◦C is rather cold” could consequently be quantified as 15◦C = [*hot*: 30%; *cold*: 70%]. Classes *hot* and *cold* are called the attribute’s fuzzy subsets.

The idea behind Fuzzy Decision Tree is thus to cut attributes into fuzzy subsets and then allowing one new instance to walk along several paths in the tree. Nodes of the Fuzzy Decision Tree are attributes (R,G,B); branches are fuzzy subsets; leaves contain the probability to belong to each decision class (Skin;Non-Skin).

Here we proceeded as follows:

1. Cut attributes (R,G,B) into fuzzy subsets using fuzzy clustering,
2. Build the tree with a training set of 80% of the data,
3. Extract rules to read the tree and test it with the remaining 20% of the data,

## 3.2 Fuzzy clustering

### 3. 2.1 Fuzzy c-mean algorithm

The fuzzy c-mean algorithm was used: it allows one point to belong to several clusters at the same time, with an associated degree of membership. The method was first developed by [Dunn et al., 1973] and consists in minimizing the following objective function:

|  |  |  |
| --- | --- | --- |
|  |  | ( 1 ) |

Where *µij* is the degree of membership of point *xi* to cluster *j* with center *cj*. *N* is the number of data points and *C* is the number of clusters to extract. *m* is the so-called fuzzifier that will give information on the degree of fuzzification (mixing) of the data. It is generally set to 2 (). The norm here represents the Euclidean distance.

This minimization is carried out through and iterative process that will update *µij* and *cj* until for every *µij*, with *k* the iteration step.

The algorithm proceeds as follows:

1. Initialize matrix with random values between 0 and 1;
2. Calculate for current step (k) the centroids vectors as follows:

|  |  |
| --- | --- |
|  |  |

1. Update *U(k)* to *U(k+1)*:

|  |  |
| --- | --- |
|  |  |

1. If , Stop. Else go to step (2).

For clarity this algorithm was described for *uij* a 1D value; here it is a vector with values (R,G,B), an so is each centroid.

Following [Bhatt et al., 2009] the clustering was first done with 5 clusters (*C* = 5). Figure 4 shows the cluster centers in the 3D representation.

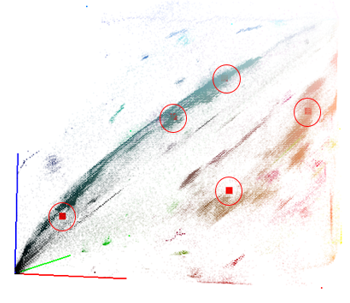


Figure :

Given cluster centers, it is now possible to extract membership functions. Membership functions allow to give a degree of membership of any point (r,g,b) for each cluster, and will be used to build the Fuzzy Decision Tree.

### 3.2.2 Membership functions

From which were extracted membership functions drawn as Gaussian curves with parameter σ = 10.

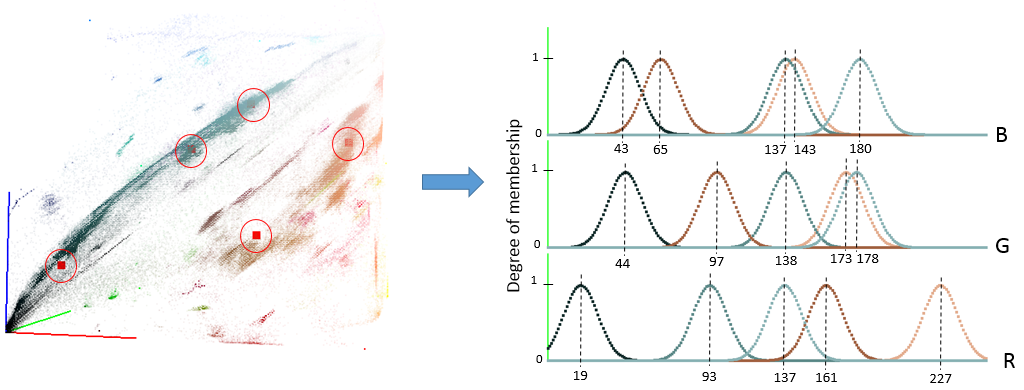


Figure : ε = 0.0005. σ = 10.

The membership functions allow to give coefficient of each fuzzy subset for any point. Their width represent the fuzziness (mixture) of the clusters: functions overlap. For example, take point p(r,g,b) = (20, 50, 50) show in figure the resulting classification !!, it can now be expressed as : ...

Visually on Figure 5, two clusters may correspond to skin color (beige and brown). However it seems like there is a wider range of colors for human skin and looking at the initial data it was assumed that more clusters could be found for skin colors. The second clustering was then increased to 10 clusters. Figure 6 shows the result for *C* = 10, with the same parameters as before.

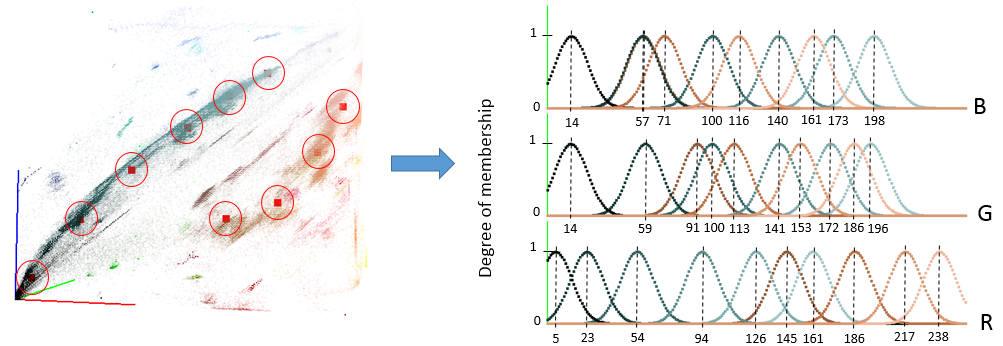


Figure : ε = 0.0005. σ = 10.

The second clustering highlighted new shades for skin color (light beige, dark brown, light brown). However the process was longer, as resumed in Table 2. In the following, the two parameterizations are used to build the decision tree and show that better results are obtained with 10 clusters.

## 3.3 Tree construction

### 3.3.1 Usual decision trees

An example of simple decision tree is given in Figure 6, where the goal is to determine which sport to play according to the current climate. The training table blablabla

|  |  |  |  |
| --- | --- | --- | --- |
| **Humidity** | **Temperature** | **Wind** | **Sport** |
| Weak | Hot | Not windy | Tennis |
| Strong | Hot | Windy | Football |
| Weak | Hot | Windy | Football |
| Strong | Cold | Windy | Running |
| Weak | Hot | Windy | Running |

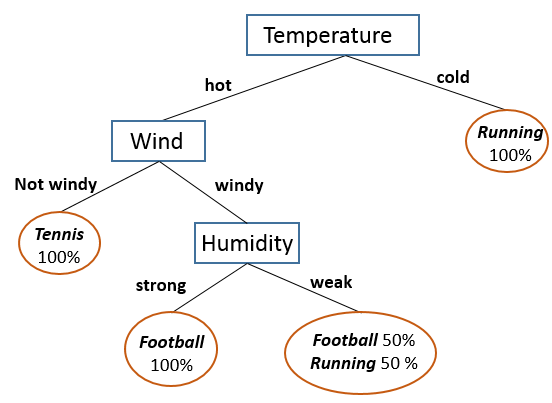


Figure : Attributes are Humidity, Temperature and Wind. Classification concerns the sport to play: Tennis, Football or Running. The reading of thetraining table leads easily to the given decision tree.

However, decision trees can quickly become hard to follow and to conceptualize with other kinds of problems (high number of attributes, classes, ...); the ID3 (Iterative Dichotomiser 3) is one of the algorithms that aim at automatizing the tree construction.

The idea is to calculate the maximum gain blablabla

|  |  |  |
| --- | --- | --- |
| **Global Entropy** | , with | ( 2 ) |

### 3.2.2 Fuzzy decision trees

A Fuzzy Decision Tree consists in nodes that are attributes, branches that correspond to fuzzy subsets and leaves that correspond to the final decision with its probability to be accurate (“truthfulness”).

In our case, the training table is given by Table 1 in the case of 5 clusters (ie. 5 fuzzy subsets). Each attribute now

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **R** | | | | | **G** | | | | | **B** | | | | | **Y** |
| µC1 | µC2 | µC3 | µC4 | µC5 | µC1 | µC2 | µC3 | µC4 | µC5 | µC1 | µC2 | µC3 | µC4 | µC5 | **Skin**/**Non-Skin** |

Table : Attributes are R,G,B. Decision class Y correspond to Skin or Non-Skin. µCi correspond to the degree of membership of the current example to the fuzzy subset i.

The tree is built on the principle of maximizing the information gain (resp. minimizing the entropy) at the creation of each node. Equations ( 3 ) and ( 4 ) give the formulas of entropy and gain in the case of fuzzy classification, for a set S={x1, x2,...,xk} with *N* decision classes *c*.

|  |  |  |
| --- | --- | --- |
| **Attribute Entropy** | ,  with membership value of *j*th pattern at class *i*. | ( 3 ) |
| **Attribute Information Gain** | ,  with the size of subset *Sv* ϵ *S* of training examples *xj* with attribute *v*. | ( 4 ) |

At each node creation, the attribute with the maximum information gain is selected. Another important issue in the tree construction is the condition to create a leaf:

1. The β *cut* is the minimal frequency of the given decision class to stop tree expansion. It is usually given between [0, 0.4] and was here chosen as 0.2.
2. The number of remaining training examples at each node has to be above a given *n*. Here it was set to 1.
3. The information gain has to be above an ε chosen here as 0.2.

Using those definitions, the FID3 (Fuzzy ID3) algorithm proceeds as follows:

1. Calculate information gain for each remaining attribute;
2. If one of this condition is met :
   1. the frequency of one class is inferior to the β cut,
   2. the number of instances is inferior *n*,
   3. all information gains are inferior to ε;

Then create a leaf and give the frequency of each decision class.

1. Else select the Attribute with the higher information gain and create a node.
2. Create one branch for each fuzzy subset. If no instances are left for one subset, do not create a branch for it.
3. For each branch, if some attributes remain, go to step (1).

In the current work, the tree was built with the free software FID3.4 (http://www.cs.umsl.edu/~janikow/fid/index.html). To do so, three types of files were generated:

* data.file gives the information about the name, number and type (categorical or numerical) of each attribute, the number of fuzzy subsets with their name, type and range, and the name and type of the decision class. The membership functions are simplified as shown in Figure 6and the 4 inflexion points are given in data.file.

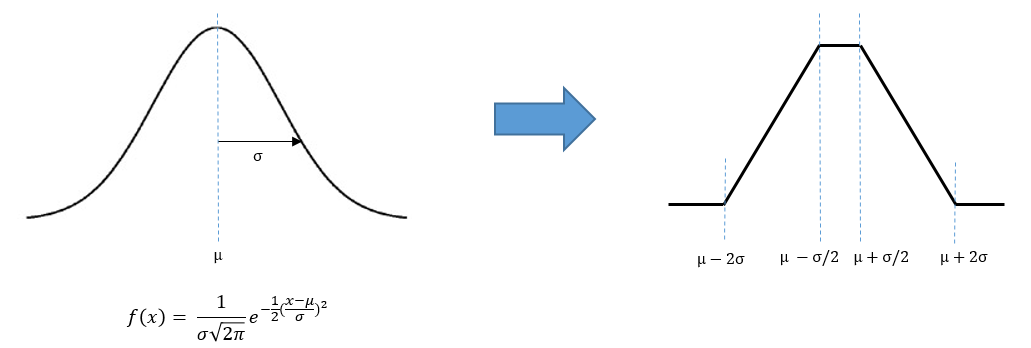


Figure : Simplification of the Gaussian membership functions for entry file in FID3.4 software. To describe the function, only 4 points are given, scaled between 0 and 1: {(µ-2σ),( µ-σ/2),( µ+σ/2),( µ+2σ)}.

* par.template contains all the parameters and options to construct the tree;
* train.file gives the training set with values for each attribute and given decision class. Here we used ... instances for training.

The output files are the following:

* tree.file reminds some information on the chosen parameters and details the tree in a compact form;
* test.file is an optional file that gives results of a testing set if a test file was given.

Example of each file are given in annex. A visual simplification of the resulting tree for 10 clusters is presented on Figure 6. The tree presents 75 leaves.

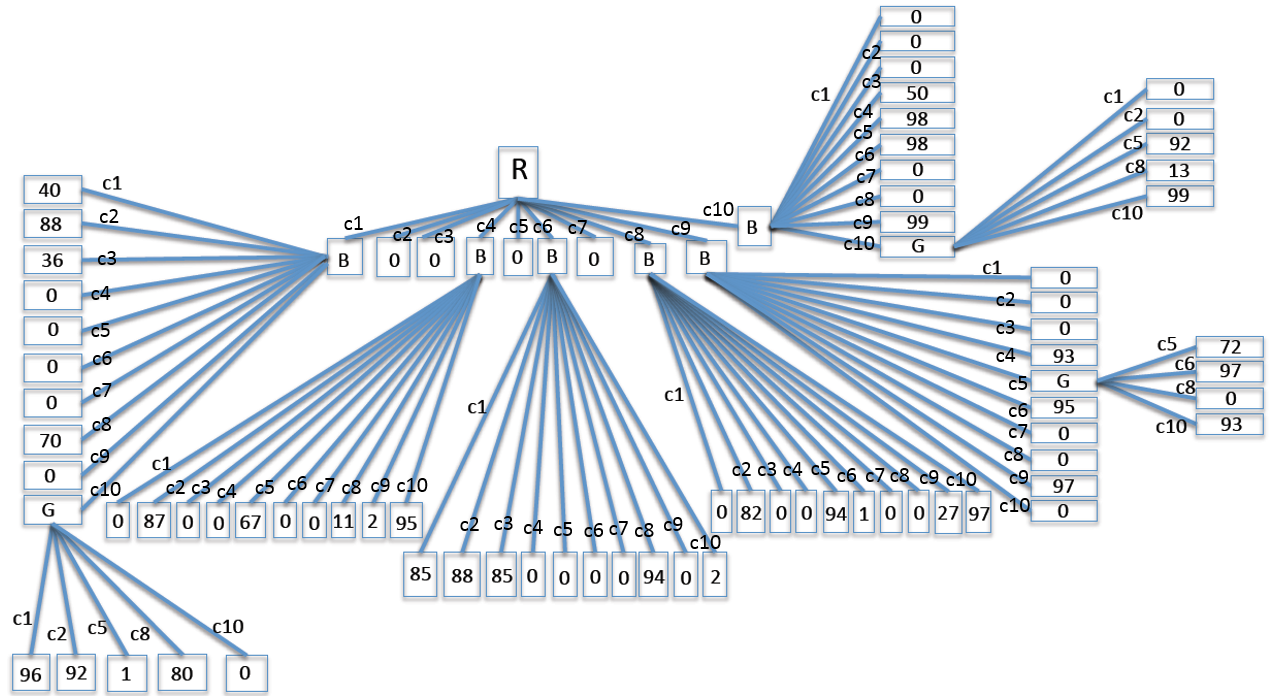


Figure : Resulting fuzzy decision tree with 10 clusters (resp. c1 to c10). The attribute with the global maximum information gain is R. Values on the leaf correspond to the frequency of decision class Skin. β-cut =0.2; n = 1; ε = 0.2.

## Testing

### 3.4.1 Rules extraction

Given a new instance, the goal is to determine the class [Skin / Non-Skin] of this instance. To do so, rules are extracted from the tree. Each path of the tree can be described with basic IF, AND, THEN rules. Taking the example of Figure 5, paths are described as follows:

* Path 1: IF hot AND not-windy THEN tennis 100%;
* Path 2: IF hot AND windy AND strong THEN football 100%
* Etc...

In the fuzzy decision tree, a new instance *e* can follow different paths and so a weight is given to each path *r*:

|  |  |  |
| --- | --- | --- |
|  | ,  With the degree of membership of *e* as regards to branch | ( 5 ) |

From here the degree of membership of *e* as regards to decision class *ck* is calculated as follows:

|  |  |  |
| --- | --- | --- |
|  | ,  with the truthfulness of decision class *ck* at the end of path *r*, that is its final frequency. | ( 6 ) |

This degree of membership is calculated for each path, and the highest membership value gives the final class chosen for instance *e*.

### 3.4.2 Example

For Example blablabla donner un example complet, on a une nouvelle instance rgb, on sort les fuzzy clusters, on regarde les paths possibles, on en deduit la classe.

### 3.4.3 Testing results

A test.file was generated with ... instances and passed to FID3.4. The given results are presented in Table 2.

|  |  |  |  |
| --- | --- | --- | --- |
| **Nb clusters** | **Clustering time** | **Building tree time** | **% success** |
| 3 | 3 min | < 1 min | < 0.8 |
| 5 | 5 min | < 1 min | 0.8 |
| 10 | 15 min | < 1 min | 0.9 |

Table : Results from cross-validation, testing tree with FID3.4 for different entries.

The best result was obtained for 10 clusters with the tree given in Figure 6. Confusion matrix is given in....

# Application to new data

The algorithm was finally run on new images where the detection of the skin can be estimated visually but where we don’t know each pixel class in advance.



Figure :



Figure :



Figure :

Conclusion

References

Rajen Bhatt, Abhinav Dhall, 'Skin Segmentation Dataset', UCI Machine Learning Repository.

BHATT, R., DHALL, A., SHARMA, G. and CHAUDHURY, S. Efficient skin region segmentation using low complexity fuzzy decision tree model. *Proceedings of 2009 Annual IEEE India Conference, pages 1–4, 2009.*

DUNN, J.C. Dunn. A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters. *Journal of Cybernetics* 3: 32-57, 1973

DONNER LES REFS SUR LES FID3 QUI EXPLIQUENT LE GAIN, L’EXTRACTION DE REGLES ETC