Virtual Whiteboard with Text Recognition and Manipulation

Abstract

Although the technical capabilities advanced a lot in education, the traditional blackboard is still in use. As a substitute whiteboards or flipcharts [1] have become a fixture in many offices, meeting rooms, school classrooms, and other work environments. One of their major disadvantages is their high cost and lack of portability.

This paper describes a system which implements a virtual-whiteboard. The physical whiteboard is replaced by the projected image of a video-projector or any kind of display (PC, Notebook etc.). The user is allowed to interact (write, draw or issue commands) with the virtual whiteboard image through an IR-LED pointer. The actions of the user are captured through the IR camera which monitors the virtual whiteboard area and are merged with the content of the displayed image. The system integrates an application for character recognition and one for text and drawings manipulation allowing an easy on-line generation of PowerPoint-like presentation

1. Introduction

According to the newest statistics [2] referring to the number of computers in the world, one can find out that 30 of 100 persons owns a personal computer at home.

Information digitalization in all domains imposes new methods of capturing, processing and displaying the information.

Traditional blackboards used in schools and also in presentations for adding additional information, tend to be replaced with a more digitalized method and why not more “clean”.

Interactive whiteboards, which vary in size and are mounted in the front of classrooms, are connected to computers. A projector shows the image from a desktop computer on a screen or board. Using an electronic pen or pointer, a teacher or student can interact with the images there, highlight or write notes on the screen, and incorporate graphics, sound, and video, the same way a desktop computer can [3].

Many different technologies can be employed by interactive whiteboards. One of the more common is infrared technology. Using infrared technology, an interactive whiteboard does not need a stylus. A finger or marker sees the infrared light projected toward the interactive whiteboard.

Infrared technology can be combined with ultrasonic technology in creating interactive whiteboards. When the marker or stylus is places on the interactive whiteboard, small sound detectors use ultrasonic technology to locate the marker's position. This technology can be used on interactive whiteboards made of any material [4].

Existing *Wiimote* (remote IR camera) systems [5] are offering only interfacing functionalities, without any post-processing or data recognition/manipulation functionalities. Touch-screen whiteboards do not provide a complete affordable functionality, the current Smart-board designers being used only as a HID whit no processing modules.

The proposed system tries to integrate most of the functionalities needed for whiteboard-like presentations: non-standard user interaction, handwriting recognition, text and drawing manipulation. The text recognition tool is introduced to avoid circular rewritings of information (e.g. something that is presented/ written can be provided to the auditors in electronic format).

The image acquisition is done by a system containing: a low-cost monochrome camera with an IR-pass filter in front of it, a standard Bluetooth technology (used to link the computer and the camera) and an IR pointer used as pen. The first two elements of the system are included in the *Wiimote* [6].

The text recognition part is realized by training a classifier with test templates, which contain images representing handwritten letter specimens for the entire alphabet. This classifier is used to recognize each hand-written character which will be used to recompose the whole text written by the user.

The text recognition part is used to create a PowerPoint-like presentation containing the interpreted text and images drawn by the user.

2. System architecture

The system requires the following components:

- *NintentoWii Remote* IR camera [6]
- Laptop/PC with a Bluetooth bundle
- IR Pen
- VideoProjector (optional)

Figure 1 describes the way in which those components communicate. The only constraints are given by the camera resolution and by the distance from which the Bluetooth can transmit/receive. For a better IR-LED detection it is necessary to place the receiver (Wiimote) at a distance of maxim 5m from the screen and at an angle, made with the screen plane, greater than 15° (Figure 1).

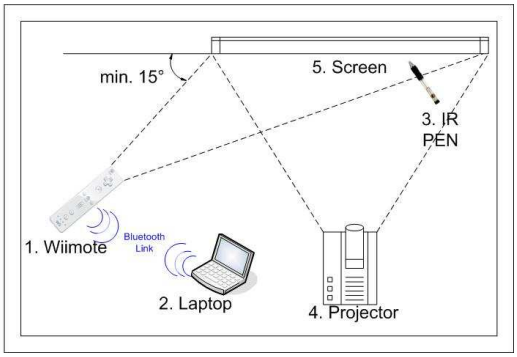


Figure 1. System architecture.

For interfacing the Wii-remote camera the library WiimoteLib [7] was used. In the current layout the Whiteboard supports only 4 user inputs at a time.

Figure 2 describes the circuit needed for the IR-LED Pen. To improve its performance a pulsed source can be used to increase the LED's intensity.

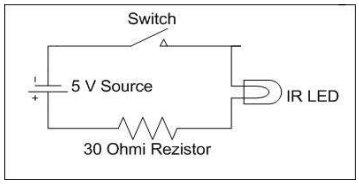


Figure 2. IR pen circuit.

The projector and the screen (4, 5 from Figure 1) can be excluded or replaced by any other image display (LCD, PLASMA-TV, LED-Display, Notebook-display).

The system is initialized through the following steps:

1. *Laptop connection to the Wiimote* is achieved by pressing together the "1" and "2" buttons (Figure 3) which enables the discoverable mode. The Wiimote will be found as a "Human Interface Device" and the Wiimote will be connected with the PC/laptop.
2. *Calibration*: the user needs to mark 4 points defining the rectangle in which the text will be written. The application warps the camera coordinates in screen coordinates. These gives high mobility to the system: the users can "write" on any flat surface.

Figure 3. Top-view of the Wiimote.

The interface for the Virtual Whiteboard with text recognition and manipulation has a central zone for text writing (Figure 4). It allows to modify the width or the color of the written text, to import/open other files having different formats needed in a presentation (PDF, doc, ppt, xls, jpg .etc). After the text is written the user can erase parts of it by using the rubber or he can clean out the entire board. After any clean up, the captured image is transmitted to the text recognition module for processing, event which generates a new thread of execution.

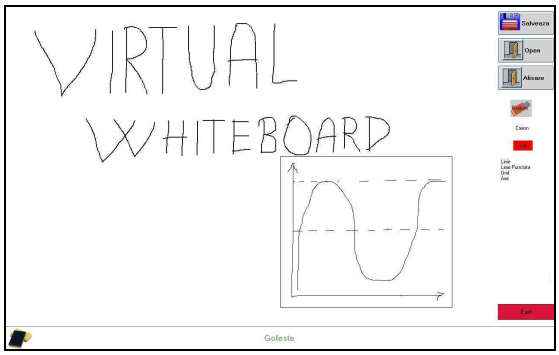


Figure 4. Virtual-Whiteboard Screenshot

At the end of the presentation the user can visualize the text written in raw format (succession of images) or converted in file format (doc, ppt or PDF) which will contain the interpretation of the written text.

3. Text recognition

Text recognition is an extensive domain which depends on many factors, each bringing a different difficulty level to the problem. Some of that are:

- The way the text is written (e.g. handwritten or capital);
- The text background (e.g. color, overlapping with other images);
- The language in which the text is written;
- The direction of the writing (horizontal/vertical);
- Width of character stroke (1px or many)
- Different (variable) font sizes;

Considering the proposed system, not all these factors have an influence. The system's use can be in presentations or courses. The entire input is on a white background and the hand-written text has a variable width of the character stroke on horizontal direction (ideal case), with different letter sizes. As favorable factors it is specified that the text is written with capital characters with letters separated with spaces. This helps to distinguish more easily each letter.

Considering these conditions the text recognition algorithm follows the next steps: image acquisition, preprocessing, letter processing, features extraction and matching (Figure 5).

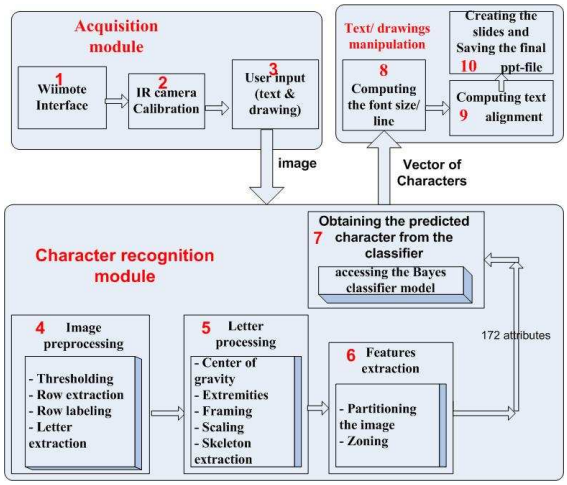


Figure 5. Architecture of the text recognition and interpretation application.

3.1 Image acquisition

The acquisition system (presented in the previous section), sends an image containing text (organized on horizontal rows) written by the user trough the IR-Led pointer. The image can contain also drawings but the character recognition application will send them further in the format in which they where found.

3.2 Preprocessing

This part refers to the way in which the image is processed, for detecting and isolating individual characters.

a) *Thresholding*: the image is scanned pixel by pixel to obtain a binary image (which contains only black and white pixels). The result is achieved by selecting a proper threshold. Pixels with intensity value greater than 128 are made white and the other ones black.

b) *Row extraction*: a partial vertical projection is used to extract from the initial image an essential slice, composed by the letters on a row.

c) *Row labeling*: to make a distinction between the letters from the same row, a labeling algorithm is used, every letter receiving a unique label. In those cases when the letter is formed by many objects (is spitted in components), each one gets the same label. If the distance between the components is smaller than H/6 (H is the height of the letter) then the objects are considered part of the same letter.

d) *Letter extraction*: from the vector of labels, the image slice is scanned sequentially for each label, the part of the image containing only one label being cropped. This crop represents all the pixels from the original image composing a letter.

3.3 Letter processing

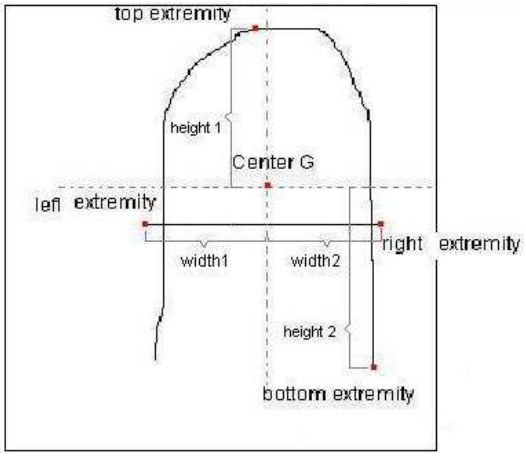
Before the detection of the features set of each letter-image crops, some processing is required. Because letters have different sizes and character strokes, the letter-image crops must be brought to a common format such that all further comparisons are made from the same point of view.

a) *Center of gravity* [8]: to avoid assuming that the center of the letter is the geometrical center of the image crop, the center of gravity must be computed. Further on, its coordinates are considered to be the coordinates of the image's center.

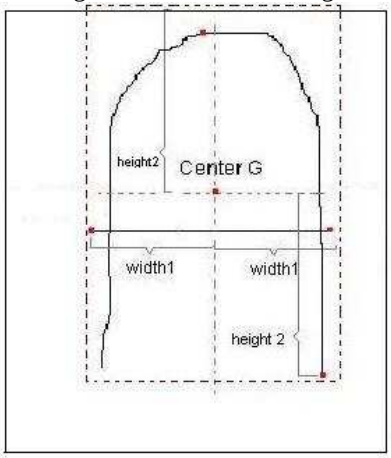
b) *Extremities*: the coordinates of the top, bottom, left and right of the letter are computed

c) *Framing*: knowing the center of gravity and the coordinates of the extremities, another crop operation is performed over the initial image crop, in such a way that the new center of gravity becomes the same with the geometrical center of the new image.

The particular case (Figure 6), in which the center of gravity of the cropped image is closer to the edges of the initial image, requires adding extra white space around the letter.



a. before framing : width 1<width 2, height 2 < height1



b. after framing: the image is cropped and the new dimensions are: (2 x width 1) x (2 x height 2)

Figure 6. a. before framing; b After framing.

d) *Scaling*: after the framing operation, the images obtained might still have different sizes, so a scaling operation is required; here the selected image size was chosen 200 x 200 (this is the average size of a hand written capital letter for a screen resolution of 1280 x 800).

e) *Skeleton extraction*[8]: the final step in achieving a standard format for the image is to transform the width of the character stroke to a unique value of 1px.

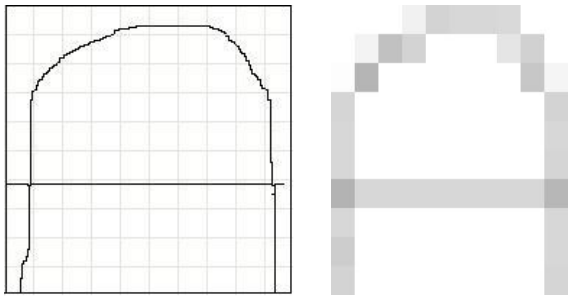
Figure 7. The skeleton of the character image [8].

3.4 Features extraction / detection

For character recognition 2 features detection methods were chosen, which are relevant in this case.

a) *Partitioning the image*: Consists in splitting the frame containing each character in sub-images with predefine sizes (because at this level all the images contain letters with the same dimensions); 20x20 pixels is a relevant dimension considering that the cropped and scaled image is 200x200 pixels (the result is 100 sub-images).

In the next step the average intensity of the pixels contained in each sub image is computed, equivalent as a fill ratio [9]; at the end will result a vector which contains all this relevant factors for every sub image from the initial image.



a. b.

Figure 8. a. image partitioning example; b. the result after computing the fill ratio at every sub image.

b) *Zoning* [9]: Through this method the frame containing each character is further divided in 3x3 sub-images. Directional histograms are extracted for each region to form an additional feature vector. The goal of zoning is to obtain the local characteristics instead of global ones.

For each zone the character's skeleton is followed and a directional histogram is obtained by analyzing the adjacent pixels in a 3x3 neighborhood using a chain-code like codification.

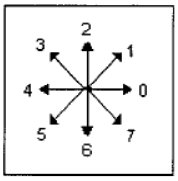


Figure 9. Chain-codes assigned to the adjacent pixels in a 3x3 neighborhood [9].

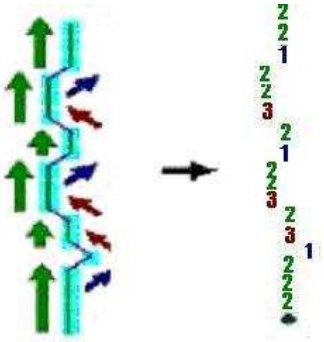


Figure 10. Generation of the direction codes by following the character's skeleton in each sub-image [9].

For each sub-image's chain code representation a histogram of the directions is built. The elements of the direction histogram from the 3x3 sub-images will form a feature vector of 3x3x 8 = 72 elements.

3.5 Classification:

For every character a feature vector of N_F=172 elements is built, obtained by combining the two feature detection methods. Considering the large number of features (N_F) a larger number of templates is needed for the training set.

The training set is used to build a classifier which uses the best features for distinguishing the letters. The large number of classes (26 letters) and the huge number of features (N_F), narrowed the research focus to two categories of classifiers: Bayes classifiers and KNN classifiers.

Statistical classification methods are based on the Bayes decision theory, which aims to minimize the loss of classification with a given loss matrix and estimated probabilities.

According to the class-conditional probability density estimation approach, statistical classification methods are divided into parametric and nonparametric ones.

a*) Bayes Decision Theory* [10]:
Assume that *d* feature measurements $\{x_1, \ldots, x_d\}$ have been extracted from the input pattern, the pattern is then represented by a d-dimensional feature vector $x = [x_1, \ldots, x_d]^T$. x is considered to belong to one of M predefined classes $\{\omega_1, \ldots, \omega_M\}$.

Given the a priori probabilities $P(\omega_i)$ and class-conditional probability distributions $(x|\omega_i)$, i= 1. . . M, the a posteriori probabilities are computed by the Bayes formula:

$$P(\omega_i|x) = \frac{P(\omega_i)p(x|\omega_i)}{p(x)} = \frac{P(\omega_i)p(x|\omega_i)}{\sum_{j=1}^{M} P(\omega_j)p(x|\omega_j)} \quad (1)$$

Given a loss matrix $[c_{ij}]$ (c_{ij} is the loss of misclassifying a pattern from class ω_j to class ω_i), the expected loss (also called as conditional risk) of classifying a pattern x to class ω_i is:

$$R_i(x) = \sum_{j=1}^{M} c_{ij} P(\omega_j|x) \quad (2)$$

The expected loss is then minimized by classifying x to the class of minimum conditional risk.

In practice, we often assume that the loss of misclassification is equal between any pair of classes and the loss of correct classification is zero:

$$c_{ij} = \begin{cases} 1, i \neq j \\ 0, i = j \end{cases} \quad (3)$$

The conditional risk then becomes the expected error rate of classification:

$$R_i(x) = \sum_{i \neq j}^{M} c_{ij} P(\omega_j|x) = 1 - P(\omega_i|x) \quad (4)$$

and the decision becomes selecting the class of maximum a posteriori (MAP) probability to minimize the error rate. The error rate $(1- \max_i P(\omega_i|x))$ is called Bayes error rate.

From equation (1) the a posteriori probability is proportional to the likelihood function $P(\omega_i)\ p(x|\omega_i)$ because the denominator p(x) is independent of class label. So, the MAP decision is equivalent to selecting the class of maximum likelihood:

$$\max_i g(x, \omega_i) = \max_i P(\omega_i)\, p(x \mid \omega_i), i = 1, \ldots M \quad (5)$$

or maximum log-likelihood:

$$\max_i g(x, \omega_i) = \max_i P(\omega_i)\, p(x \mid \omega_i) \quad (6)$$

The likelihood and log-likelihood functions are also called discriminant functions. For a pair of classes, ω_i and ω_j, the set of points in the feature space with equal discriminant value $g(x, \omega_i) = g(x, \omega_j)$ is called decision surface or decision boundary.

To make Bayes decision (or simply minimum error rate decision) requires the apriori probabilities and the conditional probability density functions (PDFs) of defined classes. The apriori probability can be

estimated as the percentage of samples of a class in the training sample set, or as often, assumed to be equal for all classes.

b) *Lazy Classifiers*->IBK [11]:

Lazy classifiers store all of the training samples and do not build a classifier until a new sample needs to be classified. It differs from eager classifiers, such as decision tree induction, which build a general model (such as a decision tree) before receiving new samples. K-nearest neighbor (KNN) classification is a typical lazy classifier. Given a set of training data, a k nearest neighbor classifier predicts the class value for an unknown tuple X by searching the training set for the k nearest neighbors to X and then assigning to X the most common class among its k nearest neighbors.

Instance-based learning (IBL) algorithms [12], [13] are a subset of exemplar-based learning algorithms that use original instances from the training set as exemplars. One of the most straightforward instance-based learning algorithms is the nearest neighbor algorithm [14][15][16].

During generalization, instance-based learning algorithms use a distance function to determine how close a new input vector is to each stored instance, and use the nearest instance or instances to predict the output class.

The distance function (or its complement, the similarity function) is used to decide which neighbors are closest to an input vector and can have a dramatic effect on an instance-based learning system.

The nearest neighbor algorithm and its derivatives usually use variants of the Euclidean distance function, which is defined as:

$$E(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2} \qquad (7)$$

where E(x) and E(y) are the two input vectors, m is the number of input attributes, and x_i and y_i are the input values for input attribute i .

This function is appropriate when all the input attributes are numeric and have ranges of approximately equal width. When the attributes have substantially different ranges, the attributes can be normalized by dividing the individual attribute distances by the range or standard deviation of the attribute

The WEKA [17] tool was used to test the above presented classifiers and to build models for each character class based on the computed features for the provided training set.

4. Text and drawings manipulation

This module uses the vector of characters computed by the character recognition component presented in the previous section.

The application calculates the proportionate font size for each line of text, taking into consideration the mean height of all letters from the current row. The alignment is computed referring to screen-dimensions, so the output document mimics the appearance of the initial written text.

When the user makes a new drawing, the system crops it from the image, and saves it.

After all these stages are completed the text and drawing manipulation module builds a new Power-Point presentation file. Each slide contains the analyzed text (with the appropriate font size and alignment) and/or the image saved from the drawings.

5. Results and evaluation

For every classifier we chose a training set of 201 templates for each letter of the alphabet (26 letters). A vector of 172 features (obtained from the 2 methods mentioned before), describes every template.

The classifiers were trained and created in Weka tool [17]. The returned results from this tool have been statistically evaluated choosing the classifier which gave the best values considering our conditions (Table 1).

Table 1. Comparison between the tested classifier's results

Classifier / Attribute	Bayes	IBK
Instances	5226	5226
Attributes	172	172
Test mode	10-fold cross-validation	10-fold cross-validation
Correctly Classified Instances	5154 98.622 %	5126 98.086 %
Incorrectly Classified Instances	72 1.3777 %	100 1.9135 %
Kappa statistic	0.9857	0.9801
Mean absolute error	0.0011	0.0019
Root mean squared error	0.0319	0.0383
Relative absolute error	1.437 %	2.5271 %
Root relative squared error	16.61 %	19.903 %

It can be seen in Table 1 that for the same test template the Bayes classifier is slightly more efficient; having the percentage of Correctly Classified Instances grater than the IBK classifier has. The most important value is that the mean of absolute error is very small 0.0011.

Another criterion that we took in consideration is the FP Rate (False Positive Rate); comparing the overall results Bayes classifier has smaller values.

The character recognition module based on BayesNet classifier was tested on a set of 5 test samples for each letter. The global evaluation of the results is presented in Table 2. The rate of the correctly classified instances was 99.359% while the mean absolute error was 0.0005.

Table 2. Bayes classifier results on the provided test sample

Classifier / **Attribute**	**Bayes**
Instances	156
Attributes	173
Test mode	supplied test set
Correctly Classified Instances	155 99.359 %
Incorrectly Classified Instances	1 0.641 %
Kappa statistic	0.9933
Mean absolute error	0.0005
Root mean squared error	0.0222
Relative absolute error	0.6676 %
Root relative squared error	11.5444 %

6. Conclusions

In this paper the Virtual Whiteboard with text recognition and manipulation abilities was presented. At first the architecture of the system was showed and the link between the components and the functionalities of the application were also indicated.

The attention was focused on the character recognition module which imposed a preprocessing level, but also a detailed feature extraction. Based on the results analysis given by the Weka tool the Bayes classifier was chosen for the characters' classification.

The results were obtained for a set of 100 features (from image partitioning) and 3x3x8 features (from zoning method) computed for a training set of over 200 templates for each character. It was demonstrated that the Bayes statistical classifier has a slightly better performance compared with a Lazy classifier (IBK).

The innovation brought by this system is that the final output result is given back to the user in a standardized format (in the current architecture a MS Power-Point presentation).

The system could be improved to analyze also the handwritten text and recognize the letters from a more difficult background.

The future developments of this application would involve using a more powerful camera and bluetooth link in order to track the actions from more than 4 users at a time. It could also use a dictionary, embedded in the text and drawings manipulation module (for increased precision in word recognition).

7. References

[1] Wikipedia, the free encyclopedia: http://en.wikipedia.org/wiki/Whiteboard, http://en.wikipedia.org/wiki/Flip_chart

[2] The Economist, *Personal Computers Getting wired*, http://www.economist.com/daily/chartgallery/displaystory.cf m?story_id=12798277

[3] M. R. Davis, - Whiteboards Inc. *Interactive features fuel demand for modern chalkboards.* September 12, 2007, http://www.edweek.org/dd/articles/2007/09/12/02board.h01.html

[4] Articlesbase, - *Looking for the Best Interactive White Board?*,Apr5th,2009 http://www.articlesbase.com/college-and-university-articles/looking-for-the-best-interactive-white-board-851887.html

[5] Hack A Day, WiiHack http://hackaday.com/category/wii-hacks/page/1/

[6] Wiimote-Wiki (Main Page) http://wiki.wiimoteproject.com

[7] Codeplex *Managed Library for Nintendo's Wiimote* http://wiimotelib.codeplex.com/

[8] Dr. E. Yfantis- *Performance Evaluation of Features Extraction Algorithms for Character Recognition*, Department of Computers Science University of Nevada, Las Vegas 05/04/2006, pp6-17.

[9] G. Vamavakas- *Optical Character Recognition for Handwritten Characters.* pp 13-17.

[10]M. Cheriet, N. Khrma, C.L. Liu, C.Y.Suen- *Character Recognition Systems, A guide for students and practioners*, Wiley- Interscience, 2007 , A John Wiley & Sons, INC., Publication,pp131-132.

[11]W. Perrizo, Q. Ding, A. Denton-*Lazy Classifiers Using P-trees*, 2002 http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.20.6476

[12]D. R. Wilson, T. R. Martinez - *Reduction Techniques for Instance-Based Learning Algorithms*, 2000 Kluwer Academic Publishers, pp 1-2

[13]Aha, D.W., Kibler, D., & Albert, M. K. (1991). Instance-based learning algorithms. Machine Learning

[14]Cover, T. M. & Hart, P. E. (1967). *Nearest neighbor pattern classification*. Institute of Electrical and Electronics Engineers Transactions on Information Theory, pp13 (1), pp21–27.

[15]Hart, P. E. (1968). *The condensed nearest neighbor rule.* IEEE Transactions on Information Theory, 14, 515–516.

[16]Dasarathy, B. V. (1991). *Nearest neighbor (NN) norms: NN pattern classification techniques*. Los Alamitos, CA: IEEE Computer Society Press.

[17]*Weka 3: Data Mining Software* http://www.cs.waikato.ac.nz/ml/weka/