Automating Graphology Using Computer Vision

Yashaswini Hosaguthi Vishwanath

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Graphology is the science of studying an individual’s personality traits through handwriting analysis. In this thesis, we have automated the graphology process, particularly automating the pattern analysis of the handwriting and inference of the personality traits. The thesis is based off computer vision techniques to build a pipeline for automated graphology using handwritten text, camera and a microcomputing device. In this work, we consider the intricate details of a handwriting sample, like the size and slant variations, the various patterns formed in the writing of the text as visual features for computer vision training and processing. Our experimental analysis on 100 users resulted in 90% overall accuracy of the system in personality trait mapping using the user’s feedback as a baseline for evaluation.

INDEX WORDS: Graphology, Handwriting Analysis, Core-region, Traits
AUTOMATING GRAPHOLOGY USING COMPUTER VISION

by

YASHASWINI HOSAGUTHI VISHWANATH

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

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Georgia State University

2020
AUTOMATING GRAPHOLOGY USING COMPUTER VISION

by

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Electronic Version Approved:

Office of Graduate Studies
College of Arts and Sciences
Georgia State University
August 2020
DEDICATION

I dedicate my work to my parents who have constantly stood beside me with love and words of encouragement. I definitely would like to thank my friends who have wholeheartedly supported me no matter what.
I am thankful to my advisor Dr. Ashwin Ashok for his guidance and insightful suggestions.

I would also like to thank Dr. Rajshekar Sunderraman and Dr. Prateek Prasanna for their valuable feedback of my research work.
# TABLE OF CONTENTS

ACKNOWLEDGMENTS .................................................. v

LIST OF TABLES ...................................................... viii

LIST OF FIGURES .................................................... ix

1 INTRODUCTION ..................................................... 1
   1.1 Thesis Research .............................................. 2
      1.1.1 Motivation ............................................. 3
      1.1.2 Problem Statement ................................... 4
      1.1.3 Approach .............................................. 4
      1.1.4 Contributions ....................................... 5

2 BACKGROUND AND RELATED WORK ............................... 6
   2.1 Background .................................................. 6
      2.1.1 Level of Socially Outgoing ......................... 8
      2.1.2 Practicality .......................................... 9
      2.1.3 degree of Optimism ................................ 9
      2.1.4 Enthusiasm .......................................... 10
   2.2 Related Work ................................................ 10
      2.2.1 Self Reports ......................................... 10
      2.2.2 Pictorial Psychological Tests ....................... 10
      2.2.3 Online Social Network Analysis ..................... 11
      2.2.4 Graphology .......................................... 11

3 SYSTEM DESIGN ................................................... 14
   3.1 Recognize 't' ............................................... 14
   3.2 System Architecture ...................................... 16
   3.3 Social Interaction Patterns ............................... 17
      3.3.1 Level of Socially Outgoing ......................... 17
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 3.1</td>
<td>Meaning of: Size</td>
<td>19</td>
</tr>
<tr>
<td>Table 3.2</td>
<td>Meaning of: Slant</td>
<td>20</td>
</tr>
<tr>
<td>Table 3.3</td>
<td>Meaning of: Degree of tolerance</td>
<td>22</td>
</tr>
<tr>
<td>Table 3.4</td>
<td>Meaning of: Practicality</td>
<td>23</td>
</tr>
<tr>
<td>Table 3.5</td>
<td>Meaning of: Degree of optimism</td>
<td>25</td>
</tr>
<tr>
<td>Table 3.6</td>
<td>Meaning of: Enthusiasm</td>
<td>26</td>
</tr>
<tr>
<td>Table 5.1</td>
<td>Precision and Recall</td>
<td>34</td>
</tr>
</tbody>
</table>
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Workflow of the automation pipeline</td>
<td>3</td>
</tr>
<tr>
<td>1.2</td>
<td>The end-to-end automated graphology concept</td>
<td>4</td>
</tr>
<tr>
<td>2.1</td>
<td>Rorschach’s inkblot(1)</td>
<td>7</td>
</tr>
<tr>
<td>3.1</td>
<td>The formation of ‘t’</td>
<td>15</td>
</tr>
<tr>
<td>3.2</td>
<td>Get the ‘t’</td>
<td>16</td>
</tr>
<tr>
<td>3.3</td>
<td>The system architecture</td>
<td>17</td>
</tr>
<tr>
<td>3.4</td>
<td>Word height v/s core region</td>
<td>18</td>
</tr>
<tr>
<td>3.5</td>
<td>Get word height of the writing</td>
<td>18</td>
</tr>
<tr>
<td>3.6</td>
<td>Core-region</td>
<td>20</td>
</tr>
<tr>
<td>3.7</td>
<td>Slant of a sample</td>
<td>21</td>
</tr>
<tr>
<td>3.8</td>
<td>Tolerant ‘t’</td>
<td>22</td>
</tr>
<tr>
<td>3.9</td>
<td>The different ‘t’s for practicality</td>
<td>23</td>
</tr>
<tr>
<td>3.10</td>
<td>T-bar</td>
<td>25</td>
</tr>
<tr>
<td>3.11</td>
<td>Mapping of features to traits</td>
<td>26</td>
</tr>
<tr>
<td>4.1</td>
<td>The zones of writing</td>
<td>27</td>
</tr>
<tr>
<td>4.2</td>
<td>Handwriting data samples</td>
<td>28</td>
</tr>
<tr>
<td>4.3</td>
<td>Stats of age v/s gender for the online data collection</td>
<td>29</td>
</tr>
<tr>
<td>4.4</td>
<td>Questionnaire response</td>
<td>29</td>
</tr>
<tr>
<td>4.5</td>
<td>The raspberry-pi set up</td>
<td>31</td>
</tr>
<tr>
<td>5.1</td>
<td>Confusion matrices</td>
<td>34</td>
</tr>
<tr>
<td>5.2</td>
<td>The trait wise accuracy</td>
<td>35</td>
</tr>
<tr>
<td>5.3</td>
<td>Accuracy per feature</td>
<td>36</td>
</tr>
</tbody>
</table>
1 INTRODUCTION

Graphology or handwriting analysis as is often called, is a modern form of psychology that identifies personality traits and human behaviour through handwriting. Just like an individual’s bio-metric, facial features and voice tone, handwriting is unique too. A graphologist can take a look at a handwriting sample written on paper or digital format to gauge manually the patterns formed to determine personality classes (ex: size, slant of the writing), estimate the category (ex: small, medium large) and further map it to traits (ex: socially outgoing, selective social groups etc). Since handwriting styles are statistically unique, a computer can reveal the author of the handwriting with high accuracy. Furthermore, using computer vision techniques it is possible to analyze what category a certain pattern belongs to. For example, determining the size of the writing of a sample, we determine whether it belongs to small, medium or high category based on the pixel sizes of the core writing. Graphology depends on a graphologist which in turn depends on their expertise in terms of accuracy and speed of the process. Incidentally, there are no end-to-end automated graphology process today. This thesis takes the advent in computer vision to delve deep into the patterns formed in the writing to determine traits of the writer. We develop techniques to automate the process of handwriting analysis by camera-scanning the handwriting sample and using computer vision techniques to extract inferences about the person. These outcome of the process is an inferred list of personality traits of the writer. The text region, lines and words are extracted respectively from the sample and best candidate words are chosen for further analysis. The patterns formed by the writings are sequentially analyzed to deduce the results i.e the traits.
Apart from behavioural aspects, the decision making and analytical skill set of an individual can be gauged using graphology which is apt for recruitment. It is claimed that the US government uses graphology in forensic evidence analysis. But the prominent application has to be in psychology which may do wonders since it helps studying the subject and understanding their behavioural pattern without even having to know or even interact with them. The 21st century is fast paced with advancements in technology boosting the pace of human lifestyle and with barely any time to spare on retrospection of life, it becomes important to balance mental health alongside norms of the day. Graphology is known to reveal the common patterns of an individual experiencing depression which can be used as self analyses tool or with right tweaking, be used by experts to study subjects. Another arena where graphology could be helpful is in predicting dyslexia.

The implications and right usage of these methods should be carefully evaluated because of the sensitive nature and applications of the subject. The average time to perform a manual preliminary handwriting analysis by a graphologist is 4-6 minutes. With our automation tool, total processing time is less than a second! With minimal number of graphologists, automation of the process will be generally useful. The system at its state-of-the art accuracy can be better than humans and it essentially eliminates the need for human intervention. Figure 1.1 shows the overall workflow of the automation pipeline.

1.1 Thesis Research

The science of graphology was learned from Handwriting Institute India (HII) headed by Rafiullah Baig, a handwriting analysis expert and coach. The HII works in junction with Handwriting University International and much of the study of the handwriting or graphol-
The process of graphology today is offline where the graphologist manually analyses the sample on paper. This process can take from 4-6 minutes for a preliminary analysis and 30 minutes for a detailed personality review. Few works are done in the field of graphology
and very few works have been done in automation and the idea of an end-to-end computer vision driven tool is novel. The potential end use cases are numerous ranging from forensics to psychology. Keeping all these in mind, we were motivated to develop a fast, accurate and automated online software tool for graphology.

1.1.2 Problem Statement

The problem we are trying to address here is automating the graphology process which is mostly offline today, with the help of computer vision techniques. In this thesis, we have explored ways to extract and analyze textual patterns formed in the writing, measure the degree of a certain pattern and map it to personality trait.

1.1.3 Approach

The camera scanned image of the handwriting is first run through line segmentation followed by extraction of words. The best candidate of the words are determined based on factors like - pixel area, width of the word contour and number of characters. Patterns such as size, slant, how letter ‘t’ is formed are further analyzed in the pixel space. Depending on the values for these patterns, they are categorized into personality traits.

Since there is no direct basis to measure performance, we set up ground truths by collect-
ing self evaluations from the users during data collection. These ground truths are compared with the tool’s results for evaluation purposes.

We have total five traits: LEVEL OF SOCIALLY OUTGOING, DEGREE OF TOLERANCE, PRACTICALITY, DEGREE OF OPTIMISM AND ENTHUSIASM each of which are mapped to levels or degrees of the trait intensity.

1.1.4 Contributions

This thesis contributes the following research outcomes:

- An automated graphology tool that provides personality trait inferences using camera images of handwriting samples.

- A diverse dataset consisting of handwriting samples from 100 users labeled with the associated self-evaluated personality traits.

- A web tool for graphology personality trait analysis.

- Implementation of the graphology prototype system on Raspberry Pi.
2 BACKGROUND AND RELATED WORK

2.1 Background

Graphology has been around since the 1600s, growing continually with many study and books written on it. During World War I, the interest in this field grew across Europe and the United States. The latter government invested significantly in graphology and graphologists. In the 1990s it was extensively used in recruitment processes, analysing the behavioural patterns of candidates.

Graphology is not new and has roots tracing back to the nineteenth century. But the first ever known book on graphology dates back to Spain in 1522. In the last century, researchers have sifted through theories and now agree upon over 100 universal traits and symbols in handwriting. In countries outside the United States especially Europe, handwriting analysis is known as graphology. In France, Europe, India, and all over the world, handwriting analysis is bundled into one field. There are different fields and different methodologies in this area. Handwriting which we see as a basis for understanding how a human behaves can be taken a step further to assess the mind, particularly in psychology. A study [4] shows the correlation between clinical diagnosis and graphology. The key links between the underlying personality traits and its manifestations in handwriting are determined, especially among children.

The Gestalt method is based on the German research in the early 1900s and is similar to Herman Rorschach’s inkblot tests. The Rorschach test is a way to analyze a person’s perceptions based on their remarks viewing inkblots as shown in Figure 2.1. It is known to
be used to detect thought disorders in cases where subjects can be unwilling to talk. Gestalt’s opinion is that the whole is greater than the sum of its parts. In terms of handwriting, it means the cumulative and holistic patterns contributes more to the traits. [5]

The trait stroke method is now most prominent. This method was coined by the scholar Milton Bunker, who wrote various books in the 1950s. He founded a training company in Chicago that was very popular in the 1950s until its demise during the mid 90s. Bunker was a scholar who took up the task of building this approach to analyzing handwriting to the American continent from Europe especially, from France. In this method, every stroke is considered pivotal and collectively builds up each time to form an overall significant feature of the writing. This work majorly is based on the trait stroke method.

To give a reasoning as to why trait stroke method is adopted for the work, let us take a look at an architectural metaphor. A Gestalt practitioner would step back 1000 feet from a building and describe a general impression. This can be useful, but one might miss the
basement, the back yard or the attic. The trait stroke practitioner would look at each wall, and slowly walk backward until the whole building was in full view. Having a micro and macro view can provide more in-depth results.

2.1.1 Level of Socially Outgoing

One of the important aspects of personality are emotions: how people respond to their feelings and their environment. The slant, size and pressure reveal the intensity and expressiveness of our emotions.

2.1.1.1 Slant

A vertical slant reveals logic and restrained emotion. These writers keep their emotions hidden; they are reserved and emotionally distant. It is not that they don’t have emotions, they do, maybe as deep as anyone else does, it’s just that they don’t express them easily.

A leftward slant signifies someone who would rather hold his emotions inside and has a fear of expressing himself. To get along with this person, you must understand that he will be emotionally cold much of the time. If you expect him to be consistently giving and expressing how they feel towards you, you are likely to be disappointed.

A hard right-handed slant signifies an emotionally expressive person. This writer needs to interact with people. He has a need to express his emotions. The further to the right the slant is, the more emotionally impulsive the person is. They give heed to emotional buttons like music and beauty, rather than logic and value.
2.1.1.2 Size

A small sized writing tells the person likes to move in selective social groups and are more prone to finding and moving in their comfort zones. These people are generally not the outgoers or risk takers.

A medium sized writing shows an ambivert who fits in varying sizes of socials groups. They can socialize and distance themselves suitable to them.

A large sized writing indicates people who move in large social groups. They need people around them and are known to social animals. The are usually the party planners and coordinators.

2.1.2 Practicality

In the letter ‘t’, goals of a person can determined by the height of the crossing of the t-bars on the stem. A low t-bar signifies low self-worth, fear of failing and low or no goals. A t-bar crossed three-fourths of the stem signifies practical goals. Ambition and high goals are signified by t-bars ob top of the stem. T-bars crossed above the stem reveal the dreamer and goals too high to be practical.

2.1.3 degree of Optimism

Revealed by a noticeable upward slant in the entire baseline and/or upward slanting cross bar of the letter ‘t’. The higher the incline, the more optimistic the person is. They are sure tomorrow will be better and always look on the brighter side of life.
2.1.4 Enthusiasm

An long stroke that makes the cross bar of the letter ‘t’ indicates enthusiasm. The longer the stroke, the higher is the enthusiasm. Enthusiasm is a key ingredient to success in leadership because it motivates others towards action.

2.2 Related Work

Personality Analysis can be done in various ways - self reports, pictorial psychological tests, online social network analysis, graphology etc. We will cover how some of these methods for formulated, its validity and usage.

2.2.1 Self Reports

Objective tests are psychological tests that takes subjects through series of questions to assess their characteristics and it is void of the rater’s bias. [6] Some of the widely used personality self-report measures are the Myers-Briggs Type Indicator and Neo Pi-R.

The Myers-Briggs Type Indicator Attitudes measures four bipolar prone dimensions: Extraversion-Introversion, Sensing- Intuition, Thinking-Feeling and Judging-Perceiving whereas the Neo Pi-R used the five factor model pertaining to- Openness to Experience, Conscientiousness, Extroversion , Agreeableness, and Neuroticis.

2.2.2 Pictorial Psychological Tests

Rorschach Test presents inkblots created by Herman Rorschach, refer Figure 2.1 [1][6] This test is also known to measure unconscious attitudes and motivations of the subject but can be prone to rater's bias.
2.2.3 Online Social Network Analysis

Personality analysis by analysing social network activities in terms of - frequency of usage, context, usage method for example scrolling monitoring, sharing of content etc all add up to the user's personality analysis.

The standard textual features like LIWC, MRC, bag of words, POS tags, and so on and standard non-textual features like personal information, demographic data, number of friends, and so on are employed. These methods combined with traditional rule based checks are widely used for online personality assessment.[7]

2.2.4 Graphology

The focus of this thesis is automating graphology using computer vision techniques. The idea of graphology has roots in some of the recent works in the space. The work in “Handwriting Analysis for Detection of Personality Traits using Machine Learning Approach” [8] uses image processing techniques to first identify some behavioral traits of the user. Techniques like - polygonization, template matching, vertical scanning the writing are used to establish the first level of classifications. These analysis are stored as feature values or rather labels which form the basis of the dataset for training. Further on, K-Nearest Neighbor (KNN) method is used to classify the writings into predefined classes and optimize it further to improve accuracy. But the accuracy of the system largely depends on the way the feature vectors which relies on image processing and its precision which has its own challenges. For example, since every individual have statistically unique writing, template matching wrt characters will not always yield good results. In our work, we build the system mostly on computer vision methods and use CNN pre-trained for text recognition to recognize the
prominent letter ‘t’.

In this thesis work, we aim to minimize any human intervention and extract all textual words/characters required for analysis through computer vision means. The character extraction is performed irrespective of the writing being cursive or hand-printed by performing image processing techniques like thresholding, thinning and skeletonization of textual information followed by segmentation based on over segmentation taking into account the character gap. The segmentation is followed by text recognition to recognize characters which are further grouped into 5 best samples which are taken as candidates for analysis. The character ‘t’ is focused majorly as it is considered in graphology to reveal most information for analysis.

The work in [9] does efficient preprocessing methods for line, word and letter segmentation. The features are extracted for each individual trait which are then converted to SVM format for training. The feature vectors extracted follow image processing on single character levels and since the handwriting text can be in varying formats and styles, the system may not generalize well. Also, on the macro level this approach is good whereas intrinsic traits for gestalt trait stroke method need much more first principle techniques to have accurate analysis.

The work on ”New Character Segmentation Approach for Off-Line Cursive Handwritten Words”, gives a neat approach to handwriting character segmentation that works well and hand printed and cursive writings. The work also addresses the problem of over segmentation among tricky characters like ‘m’, ‘w’.[10].

Our method of using rule based computer vision backed approach to graphology in an end-to-end automated fashion is to the best of our knowledge, novel in the research space.
Also keeping in mind the potential use cases of the work, we are motivated to build the system and possibly extend the work for future work in the psychological space - dyslexia and depression analysis.
3 SYSTEM DESIGN

From the time we have the handwriting sample to extracting patterns, determining the intensity of these patterns and finally mapping them to respective category in the personality trait forms the foundation of System Design. The various textual pattern analysis is categorized into five major traits which are based on the following

**Social interaction patterns**: level of socially outgoing and degree of tolerance

**Behavioral patterns**: practicality, degree of optimism and enthusiasm.

The textual pattern determination by tweaking and playing with the pixel space is how we solve the problem. The trait 'Level of Socially Outgoing' focuses on analysing the size and slant of the writing and all the letters in the alphabet contribute to these features. The core-region or the writing persistent in the middle zone of the text is taken into account forming the trait - size; whereas the inclination of all the letters to the horizontal is taken into account for the slant. We use five best candidates of word images generated in the word segmentation for this trait computation.

The rest of the traits are based on a single letter 't' which is the most important letter revealing a significant portion of details of an individual in the graphology space. The steps to arrive at 't' are listed below.

3.1 Recognize 't'

We aimed to automate the extraction of character 't' in both hand printed and cursive styles of writing. The five candidate words are further broken down into characters and 't' is selected. Holistic look at 't' is shown in Figure 3.1. The baseline is formed by marking the
lower most pixel of the start stroke and lower most pixel in the ending stroke. The start stroke leading up and down in the vertical region forms the stem of the letter ‘t’. The stems can have up and down strokes depending on how the writer writes the letter. The horizontal line crossed across the stem forms the ‘t’ bar. Also, the angle formed by the line from lower tip of the start stroke and the highest pixel tip against the baseline gives the slant of the ‘t’.

Extract ‘t’ from a word:

- Orientation correction of the line, slant correction of the line and remove shear
- Contour detection to extract minimum area coverage of the word
- Convert RGB to grayscale as we do not need the color information. Grayscale is then thresholded to get black and white image
- Noise removal by morphological operation closing(dilation followed by erosion) was performed on the word input
- Scan the word image vertically and the number of foreground pixels in each column is deduced. The column will have zero or the least value if there’s a break or least
Figure 3.2: Get the 't'

connectivity from character to character. The threshold set to decide the separating region for segmentation is 7 pixels [10]. Based on these breaks, the maximum distance possible for separation between the characters is the factor for segmentation

- Center align and add padding to each letter

- Use pre-trained CNN [11][12] for recognising 't' candidates

Figure 3.2 summarize the 't' extraction process.

3.2 System Architecture

We go through sequential methods of pre-processing and textual pattern analysis. Upon each step we get a feature. The system architecture is shown in Figure 3.3.

Once we have the handwriting image we run it through a scene text network to get textual areas. They are further sent to line segmentation [10] where any skew present is corrected. At this point the feature 5 is output. The mapping of the features to traits can be seen in Figure 3.4. Furthermore slant of the characters are determined which yields feature 2. The line is now sent to word segmentation and best candidates are passed onto determine size of the writing which forms feature 1. Next the character segmentation is called and the process of 't' extraction is done which in turn determines features 3, 4 and 6.
Let us go through each trait to understand what it means and how we go about computing them.

### 3.3 Social Interaction Patterns

Social Interaction Patterns reveal how the individual responds to social factors and environment. The key traits are measuring the level of socially outgoing a person is and his degree of tolerance.

#### 3.3.1 Level of Socially Outgoing

The size of the writing gives details of a person’s preference and interactions in social groups. The slant of the writing gauges a person’s emotional response to his feelings, situations and circumstances.
3.3.1.1 Size: Height of core-region

The core region of the writing is the textual region that covers the majority of the concentration of the writing void of upper and lower zone area. Refer Figure 4.1 to comprehend the zones of the writing. The area of the mundane or middle zone is what forms the core region of the writing. We compare the core-region of the writing to the height of the writing to get an intuition of how the actual size can be perceived if written on paper. At this stage, we have best words segmented candidates for analyzing. The way the word candidate is extracted is by drawing contour on a dilated textual image to get contour points along the boundary that engulfs one word region at a time.[13] Thus the region extracted occupies the minimum rectangular area whose horizontal spanning space gives the full span height of the writing. Refer Figure 3.4 where A is the word height of the writing and B is the core-region. When we have the full span and the core-region size AB and core-region CD, the point B-D gives the a new point E and AE becomes height, as seen in Figure 3.5.

The core-region is the region of a word image that does not contain ascenders or descenders and is bounded by the upper and the lower baseline which are the reference lines of the
word. [10] The height of the core region is the size of the writing. The consolidation of the trait and its meanings are represented in the table in Table 3.1. To compute the core region, tracking of all the black runs L() of the word image along the X axis are done. All scan lines which contain at least one black run with length greater than M are removed, where M is defined as $M = 2.5L$, where L is the modal value of all horizontal black run lengths L() [6]. The starting and end points along the Y-axis of the max of L() forms the core region. This integer (pixel) value termed as size(height of the core-region) is compared to the height of the word to categorise into - small, medium and large - if size within 30%, 50% or 70% of the height respectively. The height of the core-region is B and the height of the word is A as shown in Figure 3.4. Examples of detected core-region are shown in Figure 3.6.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Focus Letters</th>
<th>Evaluation</th>
<th>Trait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>All</td>
<td>Large</td>
<td>Usually has large social groups. People person and rarely seen alone.</td>
</tr>
<tr>
<td>Size</td>
<td>All</td>
<td>Medium</td>
<td>Can be seen in varying sizes of social groups. These people are adaptive.</td>
</tr>
<tr>
<td>Size</td>
<td>All</td>
<td>Small</td>
<td>Has selective social groups and are very particular about social appearance.</td>
</tr>
</tbody>
</table>

Table 3.1: Meaning of: Size

Algorithm 1 GetSize(wordROI)

Input : 5 word ROI candidates from word segmentation
Output : value of height
i:= Range(len(wordROI across X-axis))
L() += BlackRuns(wordROI);
L := mode(L())
fullSpan = shape(wordROI,axis=1)
M := MUL(2.5,L)
RES := RemoveScanlines(wordROI, M)
start-point, end-point = max(RES)
coreRegion = SUB(end-point,start-point)
sizes = compare(SUB(fullSpan,end-point),coreRegion, small, medium, large)
return mean(List(sizes))
3.3.1.2 Slant

The slant of the writing evaluated by finding the orientation of the characters wrt the baseline of the writing gives us - slant - which in turn gives an insight to the person’s emotional response to situations and circumstances. All the letters in the writing contribute to slant.

The slant of the writing is the inclination of the characters with respect to the baseline, where the baseline is the bottom-most row (end-point) of the core region. It is known that the angle usually lies within +/-45° to the vertical (90°). Here, -45° to 0° represents the left slant; 0° to 30° represents the mid slant; 30° and above represents the right slant.

The core region from 3.3.1 is taken where the end-point becomes the baseline of the writing. The line formed by taking the point of the origin of the first black run to the tip of the character is called the slant measurement line.(Refer Figure 3.1) The corresponding angle between this line and the baseline gives the slant. The modular value over all candidates is the slant of the writing. The consolidation of the trait and corresponding meanings are better represented in the Table 3.2.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Focus Letters</th>
<th>Evaluation</th>
<th>Trait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slant</td>
<td>All Upper zone</td>
<td>Left Slant</td>
<td>Does not express feeling and emotions easily. Is known to make firm and practical decisions.</td>
</tr>
<tr>
<td></td>
<td>letters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slant</td>
<td>All Upper zone</td>
<td>Mid Slant</td>
<td>Is level headed though there can a battle between head and the heart when it comes to decision making.</td>
</tr>
<tr>
<td></td>
<td>letters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slant</td>
<td>All Upper zone</td>
<td>Right Slant</td>
<td>very expressive and relates to others easily. Is empathetic and known to take decisions driven by emotions.</td>
</tr>
<tr>
<td></td>
<td>letters</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2: Meaning of: Slant
Figure 3.7: Slant of a sample

The slant measurement line seen in Figure 3.1 gives the pictorial representation of how to go about slant calculation. Observe in Figure 3.7 - the baseline (the bottom most row of the core region) highlighted whilst the connection between the highest point of upstroke and starting point of upstroke and the angle it makes with the baseline gives the slant.

3.3.1.3 Slant Correction

Once we compute the slant of the writing, it is beneficial to correct the slant especially if the writing is cursive.[14] Slant correction aims at eliminating the angle of writing to align best to the vertical which is appropriate to distinguish the character gap which is primal for segmentation. This step is performed right before segmentation as we now have a fine differentiation between the characters when corrected close to the vertical.

3.3.2 Degree of Tolerance

In graphology, the curve or bent nature in the ‘t’ indicates that the person has high tolerance levels. Such people let tolerance to challenging situations build over time and give various chances to situations or people. But that can lead to passive aggression and finally lashing out. The example of tolerant form of ‘t’ is represented in Figure 3.8. A steady t-bar
Table 3.3: Meaning of: Degree of tolerance

indicates in control or calmness in challenging situations. A rasp and sharp t-bar indicates less tolerance and can amount to being short-tempered. The consolidation of the trait details and meanings are better represented in the table in Table 3.3.

A t-bar that is curved in a concave shape, much like a shallow saucer - the stronger the curve, more tolerance is seen. An umbrella shape signifies the person is trying to exert deliberate control over an action, compulsion, or situation in his life.

The 't' got from 3.1 is used to compute 'degree of tolerance'. The horizontal space is spanned and hough-transform is performed to extract the t-bar lines. If there is no bent in the t-bar, the top most point in the bar will not make an angle with the end points of the line. If there is an angle present $\geq 5^\circ$ then there is bent in the t-bar. Refer Algorithm 2.

**Algorithm 2** GetTBar(letterT)

```
Input : 5 candidate letters T
Output : Boolean(True, False)
    dilated := dilate(letterT, iteration=1)
    line := HoughTransform(dilated)
    tip := GetTip(line)
    checkAngle := getAngle(line[0], tip)
    return mode(checkAngle)
```
3.4 Behavioral Patterns

Some behavioral patterns like practicality, degree of optimism towards life and enthusiasm is walked through its deductions.

3.4.1 Practicality

The t-stem is the vertical trace of the letter ‘t’ from start of the stroke to its end whereas t-bar is the trace of the horizontal line drawn across or near the stem that finishes the letter. (Refer Fig 3.1) The placement of the t-bar against the t-stem is analyzed and categorized as - low, middle and high. The consolidation of the trait details and meanings are better represented in the Table 3.4.

When the t-bar that is crossed high in the middle zone, the writer is pragmatic and level headed. They also have good self-esteem whereas lower t-bars indicate lack of good self-esteem. The principle is aim for practical things and give much decisions to the head rather than the heart.

The extremely high t-bar cross shows high self-esteem, high goals, confidence and ambitious nature of the writer. Combined with other traits like, large size 3.3.1.1) and high
enthusiasm (3.4.3), is a rare and positive trait. It means high enthusiasm topped with large social circle and high goals, this person can achieve wonders. Sir Thomas Alva Edison had such unique ‘t’ writings as seen in his handwriting. His constant failed experiments but yet the grit to go on and finally succeed in developing a first electric light that was economically manageable is no doubt commendable. Refer Algorithm 3 for the approach.

**Algorithm 3** GetTBarPos(letterT)

```plaintext
Input : 5 candidate letters T
Output : Value of t-bar levels
dilated := dilate(letterT,iteration=1)
line := HoughTransform(dilated)
height_t := shape(letterT)
checkPos := getTbarPos(height_t, line, low, medium, high)
return mode(checkPos)
```

3.4.2 Degree of Optimism

Optimism in graphology is revealed by noticeable upward slant in the entire baseline of the writing and/or the ‘t’ cross bar upward inclination. Higher the inclination, higher the optimism.

Here, the inclination of the t-bar to the horizontal is analyzed. The upward slant indicates an optimistic personality whereas downward slant indicates pessimism in graphology. The t-bar rendered from previous step 3.4.1 is taken into account with end points of the line giving inclination angle to the horizontal is calculated. The slope from these points computed indicates upward slant with positive slope whereas negative slope indicates downward slant.

The consolidation of the trait details and meanings are better represented in the Table 3.5.


<table>
<thead>
<tr>
<th>Feature</th>
<th>Focus Letters</th>
<th>Evaluation</th>
<th>Trait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Degree of Optimism</td>
<td>t</td>
<td>Upward</td>
<td>Optimism.</td>
</tr>
<tr>
<td>Degree of Optimism</td>
<td>t</td>
<td>Downward</td>
<td>Pessimism.</td>
</tr>
</tbody>
</table>

Table 3.5: Meaning of: Degree of optimism

**Algorithm 4 GetTBarIncline(letterT)**

- **Input**: 5 candidate letters T
- **Output**: Value of t-bar inclination levels
- `dilated := dilate(letterT,iteration=1)`
- `line := HoughTransform(dilated)`
- `checkIncline := getTbarIncline(line,Upward,Downward)`
- `return mode(checkIncline)`

Figure 3.10: T-bar

### 3.4.3 Enthusiasm

The steadiness and length of the t-bar indicates level of enthusiasm. The t-bar obtained in the previous step 3.4.2 is analyzed to get the length of the t-bar line by distance formula as we know the start and end points of the line. The detected t-bar is shown in Figure 13.

An unusually long 't' stroke that makes the cross bar of the letter means the writer bubbles with enthusiasm and excitement. Enthusiasm is a key ingredient to success in leadership because it motivates others towards action. As seen in 3.4.2, a high t-bar with high length of t-bar is a great combination indicating practical yet enthusiastic approach to doing things. End-to-end pipeline of mapping from features and traits are visually represented in Figure 3.11.
Algorithm 5 GetTBarLength(letterT)

Input : 5 candidate letters T
Output : Value of t-bar length
dilated := dilate(letterT, iteration=1)
line := HoughTransform(dilated)
checkLength := getTbarLength(line)
return mean(checkLength)

<table>
<thead>
<tr>
<th>Feature</th>
<th>Focus Letters</th>
<th>Evaluation</th>
<th>Trait</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enthusiasm</td>
<td>t</td>
<td>High - Steady and Lengthy</td>
<td>Have high level of enthusiasm. Is a adrenaline riven person.</td>
</tr>
<tr>
<td>Enthusiasm</td>
<td>t</td>
<td>Medium - Medium length</td>
<td>Level headed enthusiast. There is a balance in this person’s enthusiasm.</td>
</tr>
<tr>
<td>Enthusiasm</td>
<td>t</td>
<td>Low - Shorter t-bar</td>
<td>Have lower level of enthusiasm. This person can be lazy.</td>
</tr>
</tbody>
</table>

Table 3.6: Meaning of: Enthusiasm

Figure 3.11: Mapping of features to traits.
We collected the handwriting samples from more than 100 volunteers for the purpose of this research. The textual information collected was uniform, written on an A4 sheet with white background. The text content collected is carefully crafted to include necessary characters, enough number of upper and lower zone letters.

The general zones of the writing are upper, middle and lower that are attributed to philosophical, mundane and physical criteria respectively, as is represented in Figure 4.1. Letters like 'h','l','t' lie in the upper zone whilst letters like 'g','y' fall in the lower zones. The letters that just stay in the mundane or middle zone letters include 'a','e','i','o','u' whilst some letters like 'f','p' may pierce both lower and upper zones. The textual line we collected from volunteers is - "Time is ticking. It does not stop for anyone". We have 5 letter 't', 3 lower zone piercings letters - g,p and y, 8 upper zone piercing letters - t,k,d and f. This is sufficient for our trait stroke method of handwriting analysis. Some samples are shown in Figure 4.2.

Figure 4.1: The zones of writing
4.1 Data Collection

There are two parts to data collection:

- Handwriting sample with the text "Time is ticking. It does not stop for anyone" written on a paper with white background.

- Self evaluation via a questionnaire answering personality questions about self.

There are two ways to data collection: physical and online. The online collection on our website at been found at [15].

- First way is physical collection from volunteers. Second is camera scanning the sample and uploading it to our website.

- The collection is not complete without self evaluation which we further use for performance evaluation purposes. The first way is to physically collect questionnaire on printed questionnaire on paper and collect along with handwriting samples. Second way is to visit our website to fill out Google form questionnaire.
Each sample was run through scene text recognition,[16] extract text regions, sentences or lines by computer vision means and labelled sequentially where each unique integer represents the writer. Some statistics of the diversity of the data collected online is represented in the Figure 4.3.

Example of a question phrased in the questionnaire via Google form and the stats of the response is shown in Figure 4.4.

4.2 Prototype Implementation

The experiment was conducted on: Ubuntu Operating System 16.04 64 bit, 32GB RAM, NVIDIA GeForce RTX 2080Ti. The experiment was performed on more than 100 users’
handwriting. The data was collected from writings submitted by volunteers written on a white A4 paper with required text for analysis or an image version if collected online. The textual localization is performed [16] by scene text recognition. The writer was further asked to evaluate self on certain personality traits through a questionnaire on paper or an online survey via google forms, the results of which are used as a baseline for comparison to evaluate performance of the system. The writer was asked to use a ball-point pen to maintain uniform thickness of the writing which might otherwise be inaccurate. For example, using a pencil might make the writing too thin and also not result in blunt images while scanning. Contrarily if for example, markers are used for writing, the thickness might be more than needed which may also hamper the clarity of the characters formed. The text is then pre-processed to identity lines and then subsequently the words. The words are segmented into individual images which are further used for analysis of different traits.

For each of the samples, all the 5 traits were analyzed and evaluated against their self evaluation collected in the first step. The overall absolute accuracy of the model is 90% and the total execution time of the system is 0.86 second.

4.2.1 RaspberryPi - Prototype Implementation

In order to present how compact the system implementation can be and how easily it can be replicated, the system proposed was implemented on a RaspberryPi for demo purposes. This goes on to show how well the system scales on a minimalist hardware setup. The experiment was conducted on RaspberryPi 3B with CPU - 4 ARM Cortex-A53, 64-bit instruction set SoC and 1.4GHz RAM.

The end-to-end implementation from camera scanning through the PiCamera, handwrit-
ing analysis and report generation was done on RaspberryPi model integrated with the PiCamera.

The total execution time of the system with the Pi setup is 1.2 seconds.
5 EVALUATION

To comprehend how well the system performs, we derive comparison between the ground truth and predicted results. Since the nature of the problem is behavioral analysis, one cannot clearly make distinction for right and wrong results as such intangible are usually subjective. But to get a sense or get a close estimation and understanding of the performance, we went ahead with the self evaluation of volunteer subjects as basis for ground truth. The self evaluation data obtained from volunteers via questionnaire were considered as ground truth and the end result of trait mapping levels are our predicted results.

We compute following measures to evaluate performance of the system:

- For each trait’s category of result, we deduce the precision and recall
- For each trait, the accuracy of the classification of results
- Overall accuracy of the system
- For each features derived, we also check how best the computer vision model works in distinguishing the patterns

The evaluation metric - precision and recall, are defined as follows:

\[
\text{Precision} = \left( \frac{\#\text{MatchedSamples}}{\#\text{PredictedSamples}} \right) \times 100 \tag{5.1}
\]

\[
\text{Recall} = \left( \frac{\#\text{MatchedSamples}}{\#\text{GroundTruthSamples}} \right) \times 100 \tag{5.2}
\]
\[ \text{Accuracy} = \left( \frac{\# \text{AllCorrectMatches}}{\# \text{Total}} \right) \times 100 \]  

(5.3)

The Precision for a single class is the correctly classified classes of all the predictions of the class. For example, the correct number of samples classified as enthusiasm-low of all the enthusiasm-low predictions.

The Recall for a single class is the correctly classified classes of all the actual samples of the class. For example, the correct number of samples classified as enthusiasm-low of all the actual enthusiasm-low samples.

The Accuracy is the number of all the correctly predicted samples to the total number of samples processed. The All Correct Matches is typically the sum of the diagonal, defined as in equation below. The accuracy depicts how well the system is able to detect the class of a trait wrt the subject’s self analysis.

\[ \# \text{AllCorrectMatches} = \sum (\text{Diagonal}) \]  

(5.4)

To better understand the distribution of actual and predicted results for each of the trait, confusion matrix was computed. Figure 5.1 shows the confusion matrix which is a matrix of Actual and Predicted samples neatly stacked to give a sense of the classification results. Thus the diagonal always represents the correctly classified records for corresponding classes. Notice how the Traits - 2 and 4 which are Degree of Tolerance and Degree of Optimism have binary classification whereas Traits - 1,3 and 5 have three classes.

The evaluation metrics are measured using the python library scikit-learn [17]. The precision and recall calculated for each trait with equation 5.1 and 5.2 are represented in the
Table 5.1. The accuracy of the traits is shown in Figure 5.2.

The overall average accuracy of the system is determined to be 90%. Thus the system to able to correctly distinguish all the traits wrt self analysis, 90% of the time.
Overall Accuracy = \left( \sum \left( \frac{\text{TraitWiseAccuracy}_{\text{Trait}}}{\text{Trait}} \right) \right) \times 100 \quad (5.5)

= (\sum \left(0.90, 0.91, 0.87, 0.90, 0.92\right)) \times 100 \quad (5.6)

= 90\% \quad (5.7)

5.0.1 Feature-wise Performance

Accuracy based on the feature or pattern detection in terms of vision anomalies. This tells how well the algorithm has performed so far to detect the patterns and stroke information. The check on feature extraction is of importance as the latter part of the analysis is dependent on how accurate these results are. There are some outliers in the feature extraction that could our attention, for example - all letters written in caps, absence of t-bar in the letter ‘t’. Such cases adversely affect the accuracy of the system. But these anomalies are related
to the style of the writer rather than fundamental issue with the computer vision process.

We manually inspected the 100 samples to understand what affects the performance in the larger picture of the working system. Figure 5.3 and Table 5.3 illustrates the accuracy per feature.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Size</td>
<td>0.98</td>
</tr>
<tr>
<td>2 Slant</td>
<td>0.98</td>
</tr>
<tr>
<td>3 T-bar hook</td>
<td>0.96</td>
</tr>
<tr>
<td>4 T-bar placement</td>
<td>0.96</td>
</tr>
<tr>
<td>5 T-bar slant</td>
<td>0.98</td>
</tr>
<tr>
<td>6 T-bar length</td>
<td>0.90</td>
</tr>
</tbody>
</table>

What this table essentially means is that at least 2 samples did not conform to the feature extraction’s expectations. One particular case is a writer with all capital writing whose sample do not have a size or slant candidate, and non presence of small letter 't’ will also end up with no candidates for rest of the features. The t-bar length has 10 difficult candidates, most of which had lengths of the t-bars cut off during character segmentation.
6 LIMITATIONS AND FUTURE WORK

We observed from our experimentation that some of the outliers in the character segmentation occurred because of the lightness in the contrast in the ink and sharpness of the font in writing. We hypothesize that ensuring high contrast and sharp handwritten textual data can ensure all character strokes are accounted for, with highest precision.

The textual patterns detected in the writings may not always account for the anomalies or outliers that come typically with free hand writings. For example, in different individualistic styles of the writer, there maybe cases such as - t-bar present, t-bar not touching the t-stem - which are not defined in the scope of graphology and such samples will hamper the accuracy of trait detection. Other external factors such as the paper used to submit the sample can augment or decrease the quality of the writing, the background color of the paper can also affect text whilst being photographed for analysis. So we recommend our volunteers to use white background that fares well in computer vision than darker background.

The kind of pen used to write also matters in offline graphology as it also affects in automated version. For example, using a pencil might make the writing too thin and also result in blunt images while scanning. Contrarily if for example, markers are used for writing, the thickness might be more than needed which may also hamper the clarity of the characters formed. Thus we advised our volunteers to use ball-point pen for uniformity and ease of text analysis and detection. In this thesis, the stress is more on automation of graphology and on increasing the performance of the model. In this work we have tend to create idealistic and automation friendly writing samples for the sake of better analysis to focus on graphology and automation while avoiding vision limitations.
We will continue exploring the depths of handwriting analysis, particularly to reveal deeper or micro traits of the person. We will explore other features relevant to writing pressure, thinking patterns deduced from letters ‘m’ and ‘n’ etc and give deeper traits. In addition, optimization on current features with bettering the pre-processing for generalizing the analysis for hand printed or cursive writing will constitute the next phase of this research.

Other areas we are interested in exploring are in - dyslexia and depression. Graphology overlaps with dyslexic analysis in terms of personality assessment pertaining to mood swings, conflicting ideals. Graphology can especially be useful in depression analysis as many pointers in the writings styles of a depressed subject can be revealed in graphology.
7 CONCLUSION

This thesis designed a novel graphology tool that can infer a person’s personality traits from a camera image sample of their handwriting. This thesis developed techniques that map visual features extracted from the handwriting image samples with personality traits as per the graphology science. The experimental evaluation over 100 users showed that the system is accurate up to 90% accurate in mapping the handwriting to personality traits of users. The ground truth for this study was captured using a self-evaluation study that asked personality and behavioral questions to each user, who answered through their ratings or scores on each question. The evaluation results also revealed that the importance of the pre-processing of the images, which contributed towards the accuracy of the system. The tool developed in this research thesis presents the foundation for graphology automation for future research in this space.

With this study we realise the social interaction patterns and the behavioural patterns of an individual whose handwriting sample is available. The pre-processing is important and contributes towards the accuracy of the system. The methods to extract further patterns in the writing are generalized as much to work on unseen handwriting samples.
REFERENCES


