M.Eng. Electrical

A DIGITAL METHOD FOR GENERATING A REFERENCE POINT IN A FINGERPRINT

by

Richard P. Karasik, B.S.E.E. (Tufts University)

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Three methods of automatic fingerprint analysis are examined. One is based on Blum's shape descriptors and attempts to classify a fingerprint by its gross shape characteristics, much like the primary classification of the Henry system. The second method, proposed by Paolantonio, uses random search techniques in order to identify a fingerprint.

However many researchers feel that the location of a reference point is of prime importance in automatically classifying fingerprints. Therefore, the technique primarily examined in this work is adapted from an analogue method suggested by Rabinow Electronics which purports to locate a reference point. The proposed digital method is essentially a gradient technique of hill climbing if the ridges are viewed as elevation contours. Trajectories are forced to travel through the fingerprint such that a trajectory always crosses a ridge orthogonally. The common intersection of these trajectories is called the reference point.

This technique was applied to 150 fingerprints. The method did locate reference points, but it was found that these were not unique. Instead, experimental results indicated that a line of maximum curvature was present. Such a line is defined by Hankley and Tou in their work on automatic fingerprint analysis. However, Hankley and Tou's method deals only with selected, partially prefiltered data. Therefore, further investigation into the line generating properties of the digital method, in conjunction with Hankley and Tou's topological method, would perhaps be the next logical step in the research into automatic fingerprint analysis techniques.

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A thesis submitted to the Faculty of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of
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Department of Electrical Engineering
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CHAPTER I

INTRODUCTION

No match has ever been found between two fingerprints, whether from the hands of different persons or from different fingers of the same pair of hands. The fingerprint is thus the unique descriptor of the individual.

No one knows when man first noticed the fine tracings on his fingers. Long before they are used for identification of the individual they were used as signatures on works of art, deeds, bills of sale, and other legal documents.

The first recorded use of fingerprints for identification purposes was in British Colonial India, where Herschel - and later Henry, after whom a modern classification system is named - registered prisoners by their fingerprints. Today, fingerprints are routinely taken and classified not only for criminal identification but for a positive identification of the general public. In the field of genetics, fingerprints are being studied as indicators of genetic deficiencies[5,20,22] (see Appendix A).

The huge lot of fingerprints that must be handled in classification centres every day is fast becoming an overwhelming problem. For example, the United States FBI maintains 177,000,000 records and is requested to classify and/or identify approximately 26,000 records per day. At present this work is done manually.

This thesis investigates the work that is being done and that is to be done in automatically classifying fingerprints by the use of those techniques that are encompassed by the term pattern recognition.

The second chapter presents some general concepts of pattern recognition in relation to automatic fingerprint analysis.

The present, manual Henry system is discussed in Chapter III. Also, some of the problems that plague this system are examined.

Chapter V presents an in depth analysis of the most representative methods of those discussed in the previous chapter. The techniques examined herein are analysed in a non-machine context in order to determine the feasibility of designing a digital computer program for one of them.

The digital method for generating a reference point in noisy fingerprints is presented in Chapter VI. The method described was chosen because of the favourable results obtained from the analysis of this technique in Chapter V.

In Chapter VII, the results and conclusions obtained from experiments carried out using the digital method described in Chapter VI are presented and discussed.

In conclusion, a digital method designed to generate a reference point in a noisy fingerprint is presented. Also included is a survey of the current literature on automatic fingerprint analyses. Finally, areas for further research into the problems associated with automatic fingerprint analysis are proposed.

CHAPTER II

PATTERN RECOGNITION

2.1 General Thoughts

The concept of pattern recognition is multifaceted. Some works in pattern-grokking* see only its practical applications to a particular problem. These applications generate 1001 different algorithms, yet entertain only a small part of the concept of pattern-grokking. Each algorithm so generated is peculiar to one particular problem, and is in general not interchangeable with another. Others in the field, noting that certain tricks - heuristic "rules of thumb" - can be applied to certain problems, try to generalize a heuristic to a gestalt philosophy in an attempt to encompass the concept of pattern-grokking. To quote an authoritative work:[16]

> Pattern recognition has been the subject of an extensive series of papers by many authors who purport to set the problems into a general framework. But the predictive value of current formulations of pattern recognition theory is near zero, and the validation of some of the claims by any objective criterion, has been meager...

In other words, in pattern-grokking there is a big space between the algorithmic and gestalt limits. This space is not easily relegated to the realm of purely philosophical discussion since the researcher's point of view is not totally philosophical.

Pattern-grokking is a field closely allied to many other disciplines yet is a distinct entity. Like psychology, it is neither an exact science, nor completely an art. Both fields use scientific techniques and methods for data collection, but it is the interpretation of this data - not so much the application of science to data collection - that

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* Grok, a Martian term used by Robert Heinlein, encompasses and goes beyond the English concepts recognize, identify, understand and comprehend.[13]

is important.

The fallacy of assuming that using scientific methods implies the existence of an exact science is partly illustrated by the story of an experimenter who placed a flea on a table under a large magnifying glass, proceeded to remove its legs one at a time, and after each operation commanded "Jump". Each time, the flea jumped. When the experimenter removed the flea's last leg, however, and said "Jump", the flea did not jump. The obvious conclusion is that a flea without legs cannot hear.

In the exact sciences we are used to ideas presented in terms of a preset theoretical framework. In a pseudoscience such as psychology or pattern-grokking, however, no prefabricated theoretical framework exists. Thus, it is up to the researcher to not only apply scientific methods of observation and data collection but to try to draw 'correct conclusions' from his observations. In so doing, the researcher forms the theoretical framework for his exact science-to-be.

So, with the reservation that pattern-grokking is not an exact science, we now try to describe some aspects of it that are applicable to fingerprint classification and identification.

2.2 Distinctions

Two important words to be noted in the previous section are algorithm and heuristic. An algorithm is a general procedure for solving a given type of problem. A heuristic is a rule of thumb, or trick - essentially a flash of insight - that makes it easier to solve any particular problem.

Most of the fingerprint classification schemes discussed in this paper are essentially algorithmic. A few, although basically algorithmic, are directed by heuristic considerations.

2.3 Definition of Descriptive Terms

Two terms will be used to help explain various identification schemes. These are the 'Tourist' syndrome and the 'Forest-for-the-Trees' syndrome.

2.3.1 The 'Tourist' Syndrome

It has been observed that many travelers arriving in a strange city tend to draw such comparisons as: "My, isn't that blank just like the blonk we have back home!" Or, in the restaurants: "You know, lux tastes just like lox."

Perhaps human beings experience life in terms of fuzzy sets, where in one context blank definitely belongs to set A, and in a different context may belong to set A but may just as likely belong to sets B,C, or D. The important thing is context. Consider eating. Various countries have various rituals or ceremonies for the partaking of food. The 'problem' is ingestion, but the context - country, rituals, people - determines the solution.

In terms of fingerprints, the idea of a contextual definition of the problem may be a bit clearer. Fingerprints are currently classified manually, according to the Henry Ten-Finger System. We want to classify fingerprints mechanically, so why not have the machine use the Henry system?

There is no pat answer to the questions "Why/Why not use the Henry system?" but a rationale does exist.

The rationale for the "why not" is as follows. Man can classify fingerprints by the Henry system; the logical starting place for machine classification schemes is thus the coding of the Henry system into the Machine.

The rationale for the "why" is that the Henry system was developed in the context of the Human pattern recognition system. The Machine pattern recognition system is in a different, if not totally alien, context; perhaps a deeper study of the problem is needed before a logical starting place can be determined.

Thus, the problem - to identify and classify fingerprints - exists. Two contexts for problem-solving exist - Human and Machine - and the problem is already solved in one context.

The 'Tourist' syndrome typifies the researcher that applies one technique to solving all similar problems, whether defined in one or in two different contexts, the solution known in one context being the basis for the solution in the alien context.

2.3.2 The 'Forest-for-the-Trees' Syndrome

A forest is made up of trees, and trees are made up of molecules, and molecules are made up of atoms. But to say that knowing the atom identifies the molecule, and that knowing the molecule identifies the tree, and that knowing the tree identifies the forest, is of course absurd.

The forest is made up of an arrangement of trees - a pattern - which in part identifies the forest. An algorithmic approach to identifying the forest would be to separately classify each tree - by a name - and perhaps measure the distances between the trees. This would involve a lot of time and effort in classifying trees, when a simpler identifier for the forest - a heuristic - might be found. It is up to the researcher to see if the simpler identifier can be found. The primary reason for 'tree classifying' is to allow for a higher resolution of classification of forests.

In fingerprint classification, the final identification depends on the minutiae (trees) of the fingerprint (forest), such as breaks in lines, joinings, endings, and bifurcations. The initial identification, however, depends only on a gross descriptor of the fingerprint.

The 'Forest-for-the-Trees' syndrome typifies the researcher that requires too much of the available information to reach a conclusion.

CHAPTER III

FINGERPRINT CLASSIFICATION METHODS

3.1 Manual Systems

The manual classification system used in most of the world today is the Henry system, named after Sir Edward Richard Henry. This system is a topological algorithm, invariant under rotation, translation, or distortion. The classification scheme is based primarily on the pattern types found in each finger. The Henry system is a ten-finger classification method, however, which means that classification cannot be effected unless all ten fingerprints are available in a specific order.

Figure 1 shows an idealized set of basic patterns and gives their frequency of appearance[6]. Figure 2 shows a good set of real fingerprints separated according to the Henry system classification[32].

In practice the fingerprints are first classified on the basis of whether or not a whorl pattern appears in the finger. This gives 2^{10} (=1024) primary classification categories. The secondary classification depends only on the pattern types found in the index fingers of both hands.

More classification groups exist, such as the small letter subsecondary, and the subsecondary, but since many intricate and involved rules apply to these classifications, they will not be considered further.

The final identification classification depends on the detailing of the minutiae and ridge counts. Figure 3 illustrates the various minutiae[32], and Figure 4 illustrates a ridge count[32]. In both figures the fingerprints are idealized. Note the line running almost diagonally from the lower left corner toward the centre in both figures. The two circles

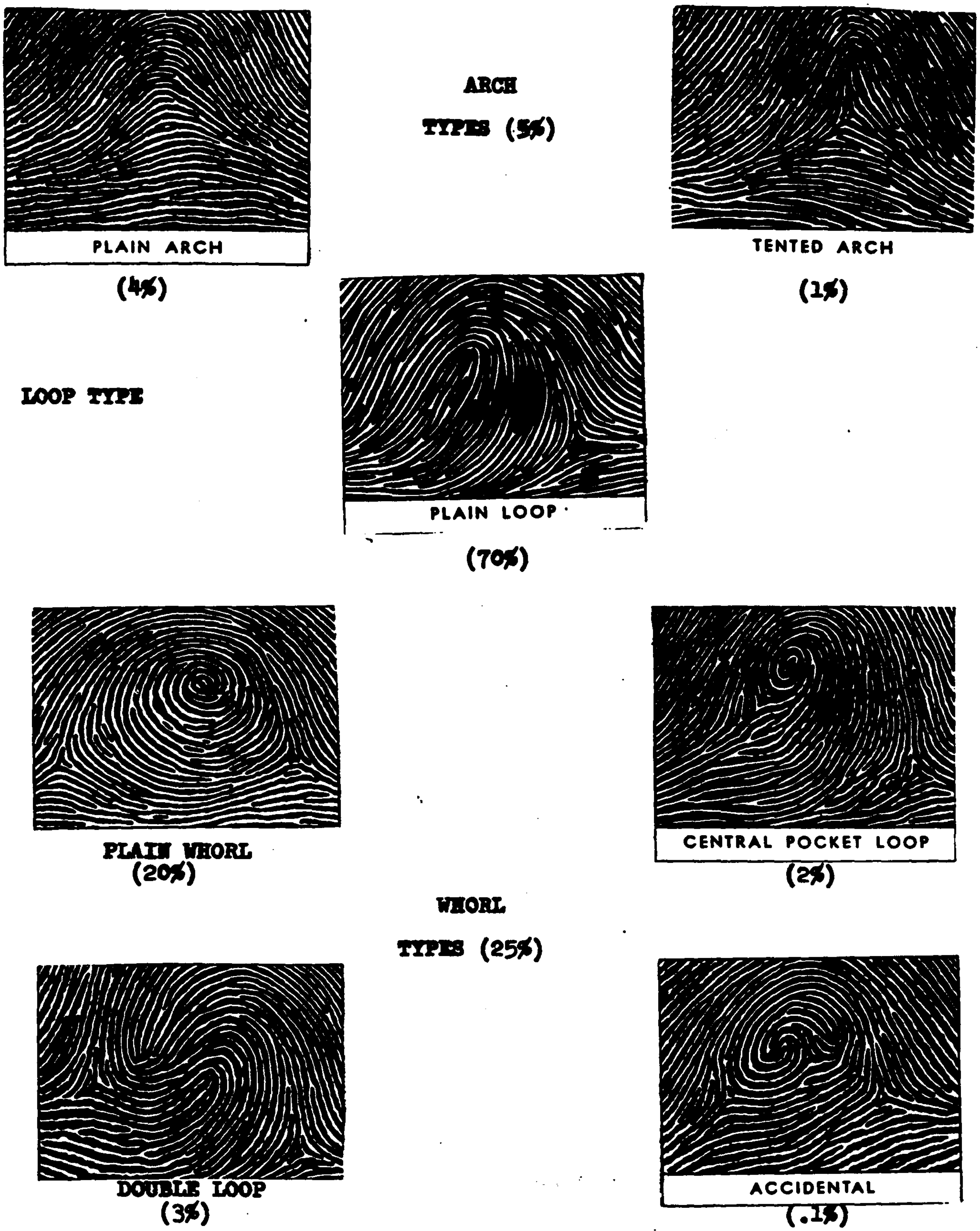
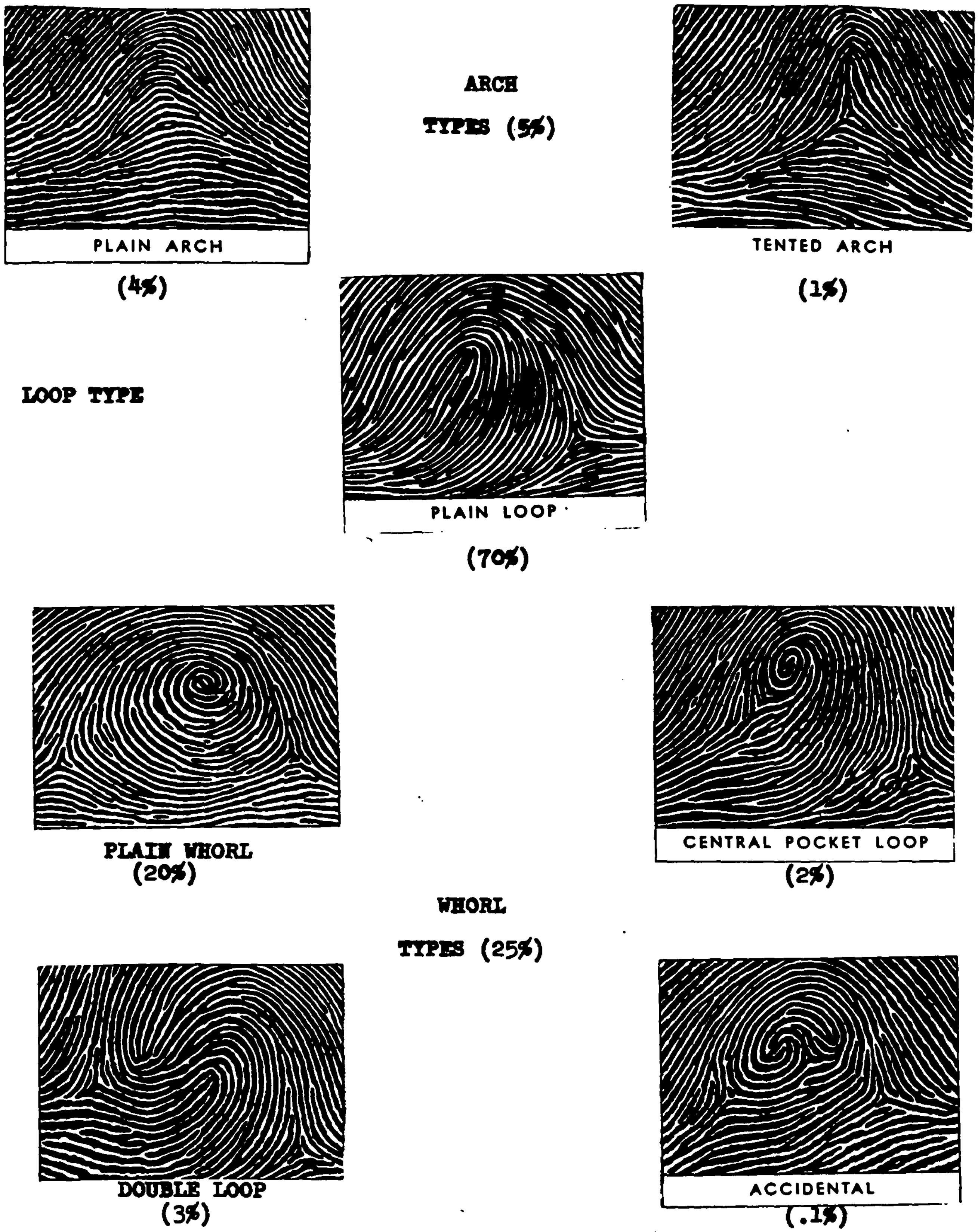


Figure 1 Examples of the Basic Fingerprint Patterns[6]

(The percentage figures indicate the frequency of each type of pattern.)



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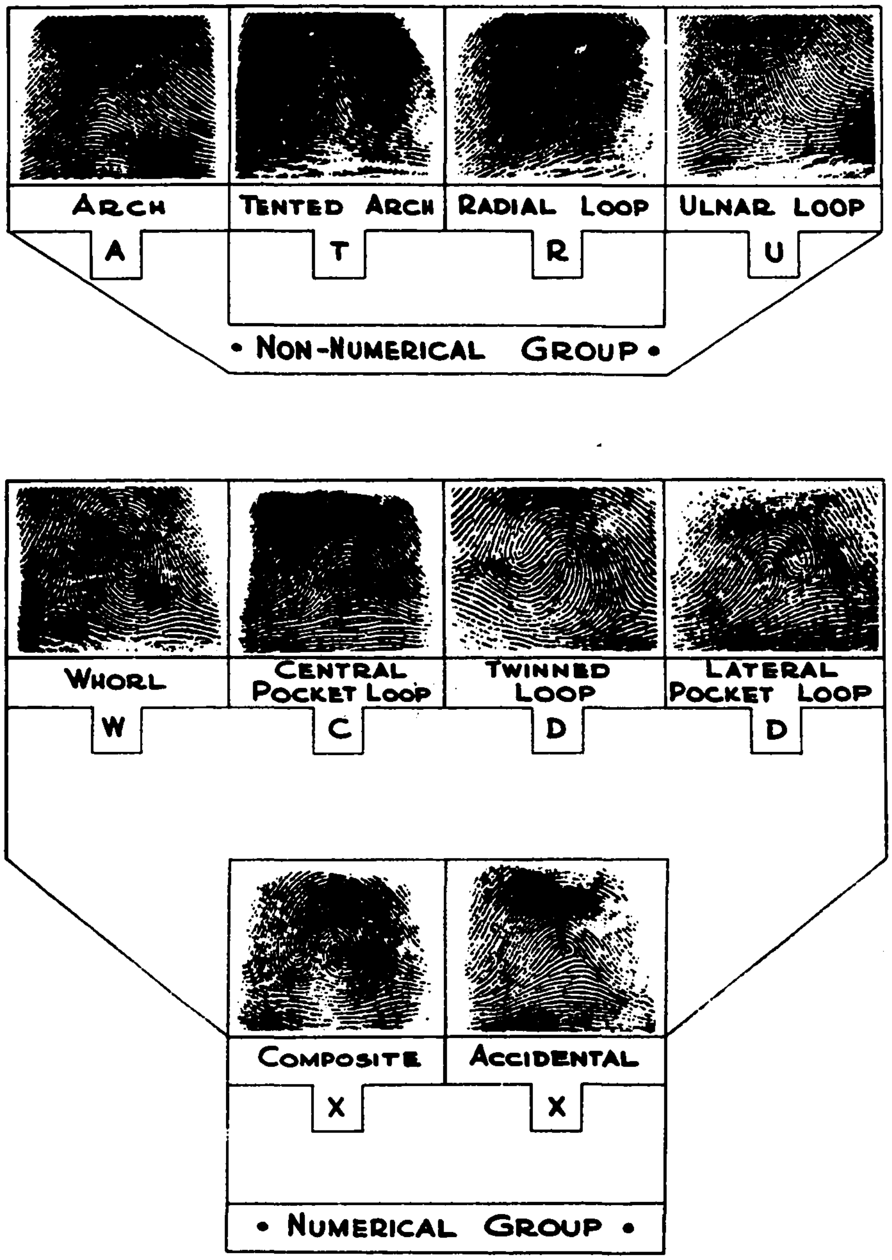
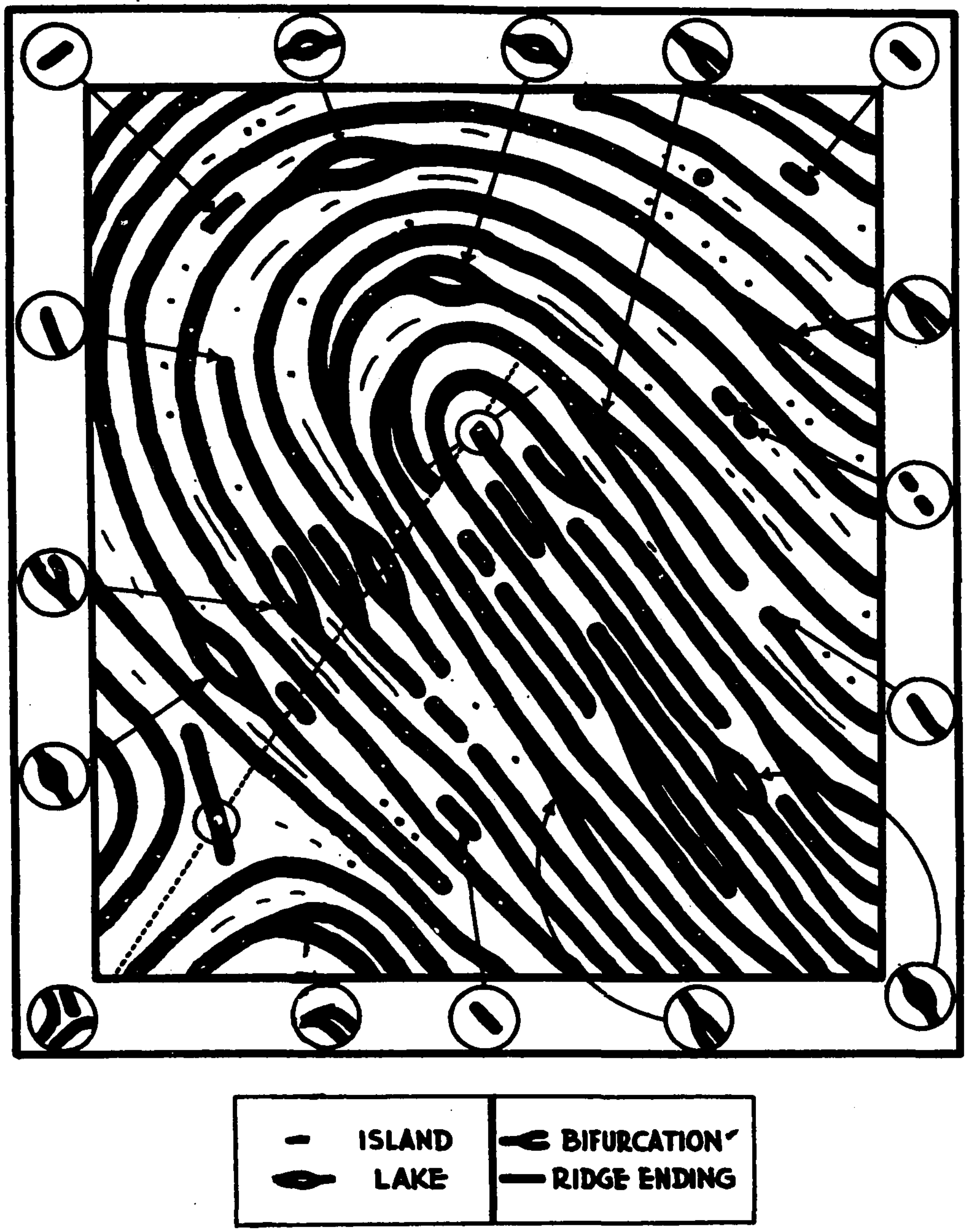


Figure 2 Types of Fingerprint Patterns[32]



<u>Figure 3</u> Various Minutiae[32]

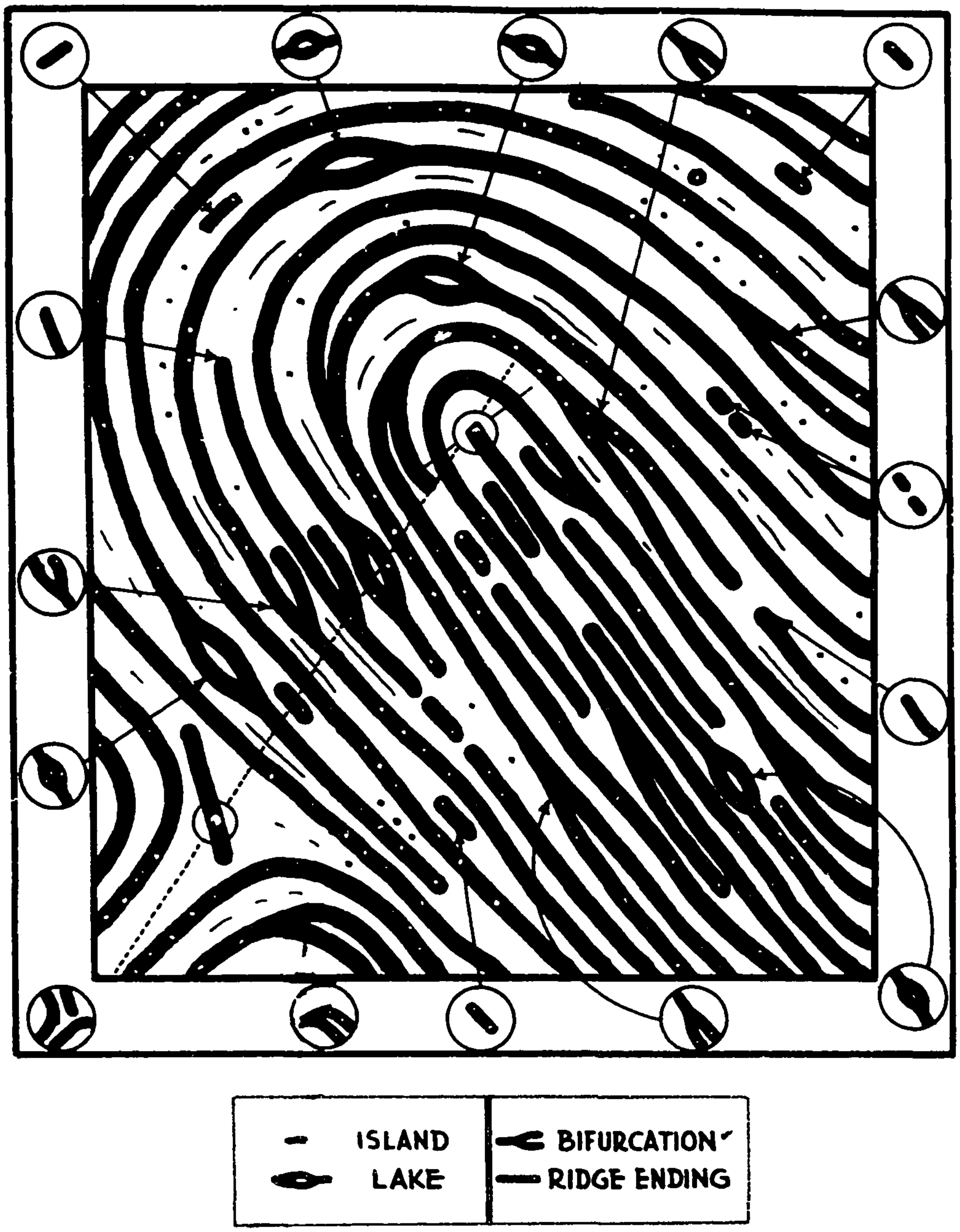


Figure 3 Various Minutiae[32]

Figure 4   A Ridge Count[32]

Figure 4 A Ridge Count[32]

on these lines indicate the two most important reference points of the Henry system. The circle at the lower left is a point of 'delta', and the central circle is a point of 'core'. The formal definitions of delta and core are quoted:[32]

> "The point of delta is the first island, ridge or ridge particle in front of the divergence of the two innermost ridges which runs parallel and diverge. When a single ridge bifurcates, the point of Delta is located directly upon the point of bifurcation, provided that this single ridge lies between the two innermost ridges which run parallel and diverge.
>
> In the loop, the core is on the innermost recurving ridge at a point on the outer side of that ridge which is furthest from the delta and where said ridge meets the recurve or on some ridge ending within the recurving portion (cap area) of the innermost looping formation."

These definitions are included, not to confuse the reader, but to show the typical algorithm the human pattern-grokking system uses with respect to fingerprint classification.

Points of core (C) and of delta (D) are indicated in Figure 5 for a variety of idealized cases[32]. Further classification considerations are:[32]

> The arch pattern does not contain a point of delta. The tented arch may or may not contain a point of delta. Radial and ulnar loops each have one point of delta. Whorls, central pocket loops, twinned loops, lateral pocket loops and accidentals contain two points of delta. The composites may have from one to three points of delta.
>
> The loop pattern is the only pattern in this ten finger system that requires the locating of the point of core, as well as the delta, for classification purposes.

Since the arch is the only pattern that has neither core nor delta, it is uniquely defined by those conditions. Thus, in general, the absence of a specific piece of information may be just as important a classifying agent as the presence of a specific piece of information.

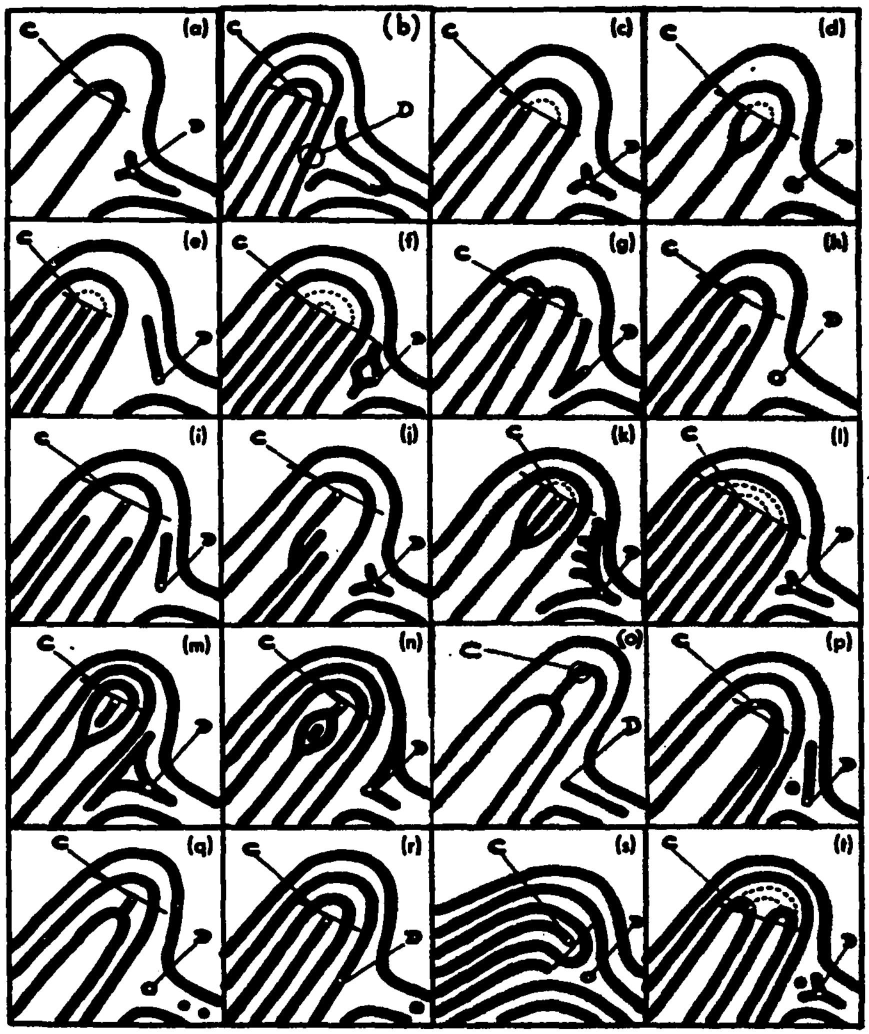


Figure 5 Points of Core and Points of Delta[32]

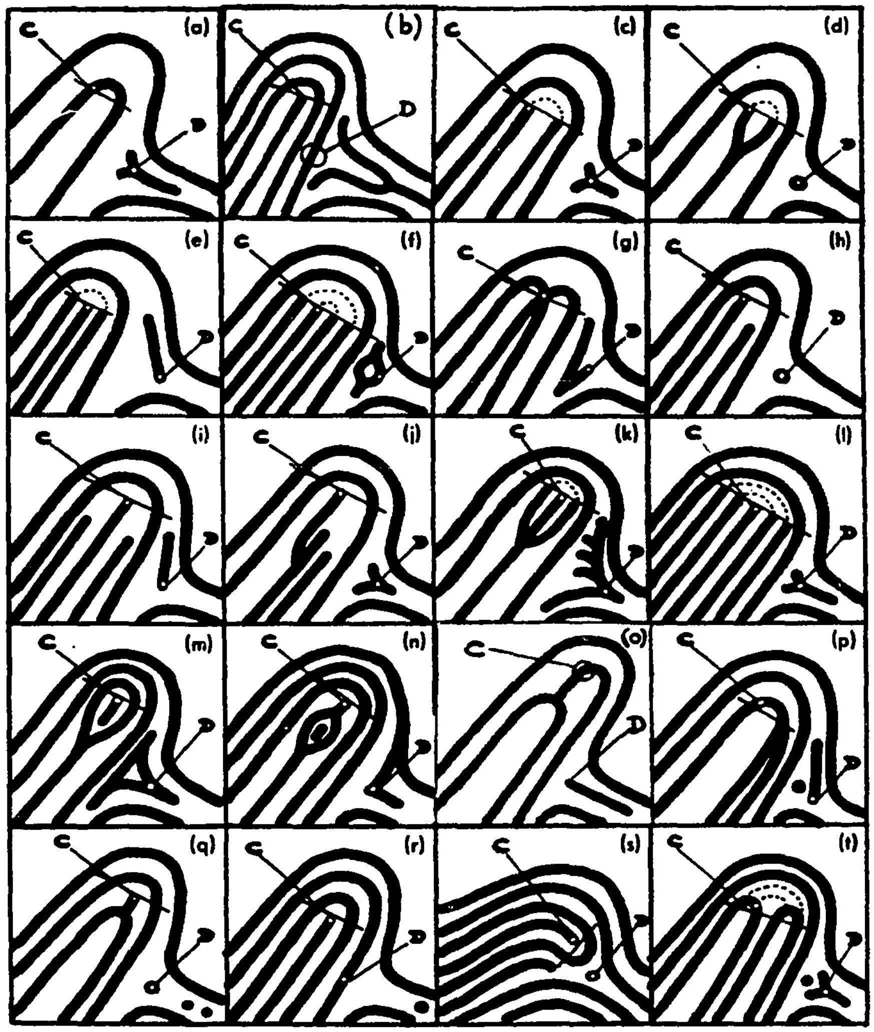


Figure 5 Points of Core and Points of Delta[32]

3.2 Problems Associated with the Henry System

One problem, noted in Section 3.1, is that there are 1024 primary classification divisions. The fingerprint types, however, are not evenly distributed among the 1024 divisions. Some of the primaries may occur in only a few hundred records, whereas other primaries may occur in hundreds of thousands of records. Because of the unevenness in distribution, it takes a relatively long time to fully identify prints from well-populated primaries. Furthermore, although fingerprints are manually classified in about 60 sec. per print, manually matching newly classified prints with those in a master file may take hours.

An automated Henry system may not be able to decrease the classification time but it can uniformly decrease the identification search time by orders of magnitude, depending on the reference or filing system used. The filing system can be made to accommodate man-machine interchanges.

Another problem is that there are five types of fingerprint impressions. Two are categorized as voluntary direct inked prints. The other three are secondary impressions obtained, for example, from objects found at the scene of a crime.

Inked prints are of two types: the rolled impression and the dab impression. These impressions are made on a fingerprint form, with special ink used as a medium. Figure 6 illustrates rolled and dab impressions.

Offset impressions taken at the scene of a crime are of three types: (a) latent, those requiring some type of developing to make them visible to the human eye, (b) visible, those not requiring development (commonly found in blood, dust, or other such media); (c) moulded or indented, also requiring development (found in putty, plasticene, or semidry paint).

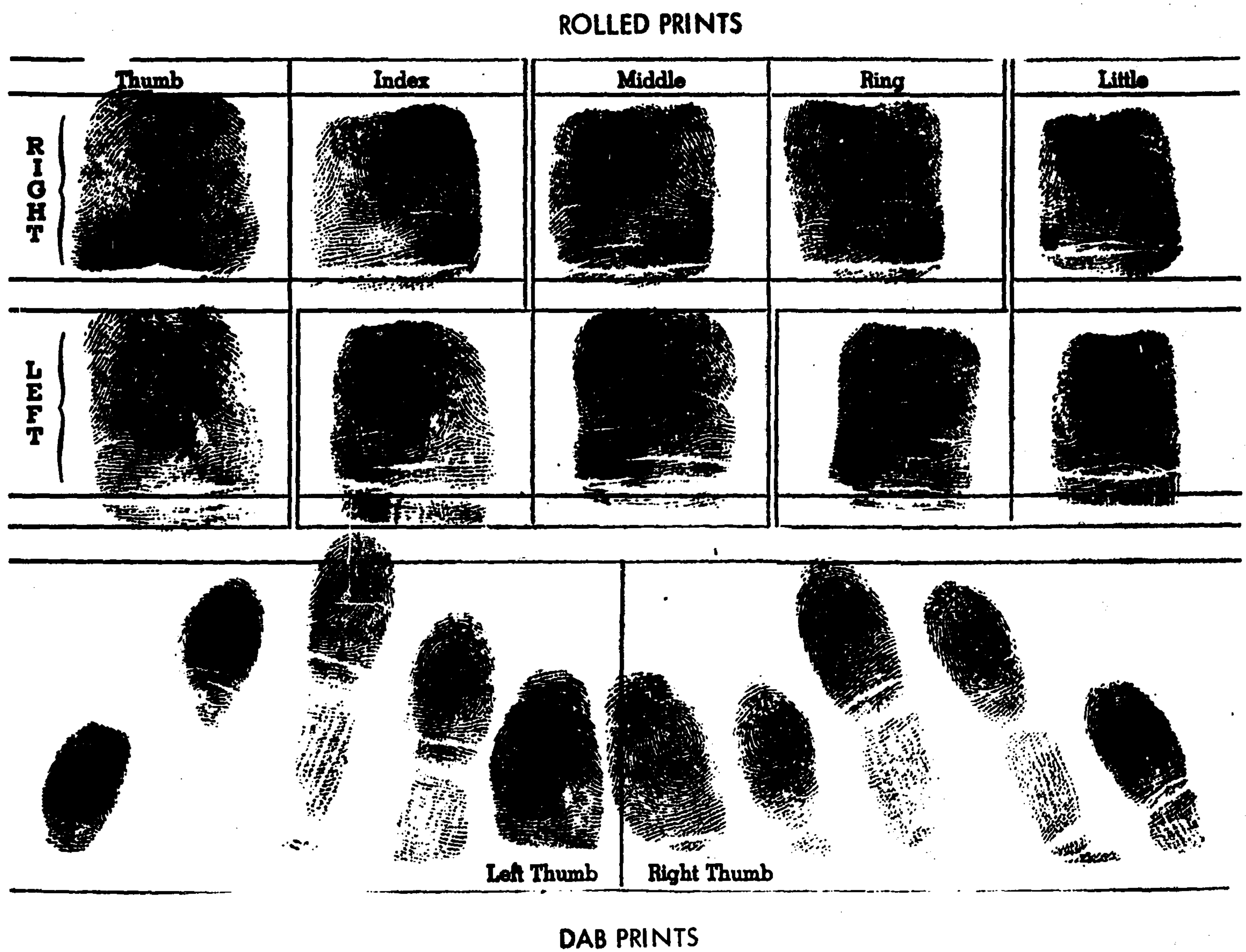
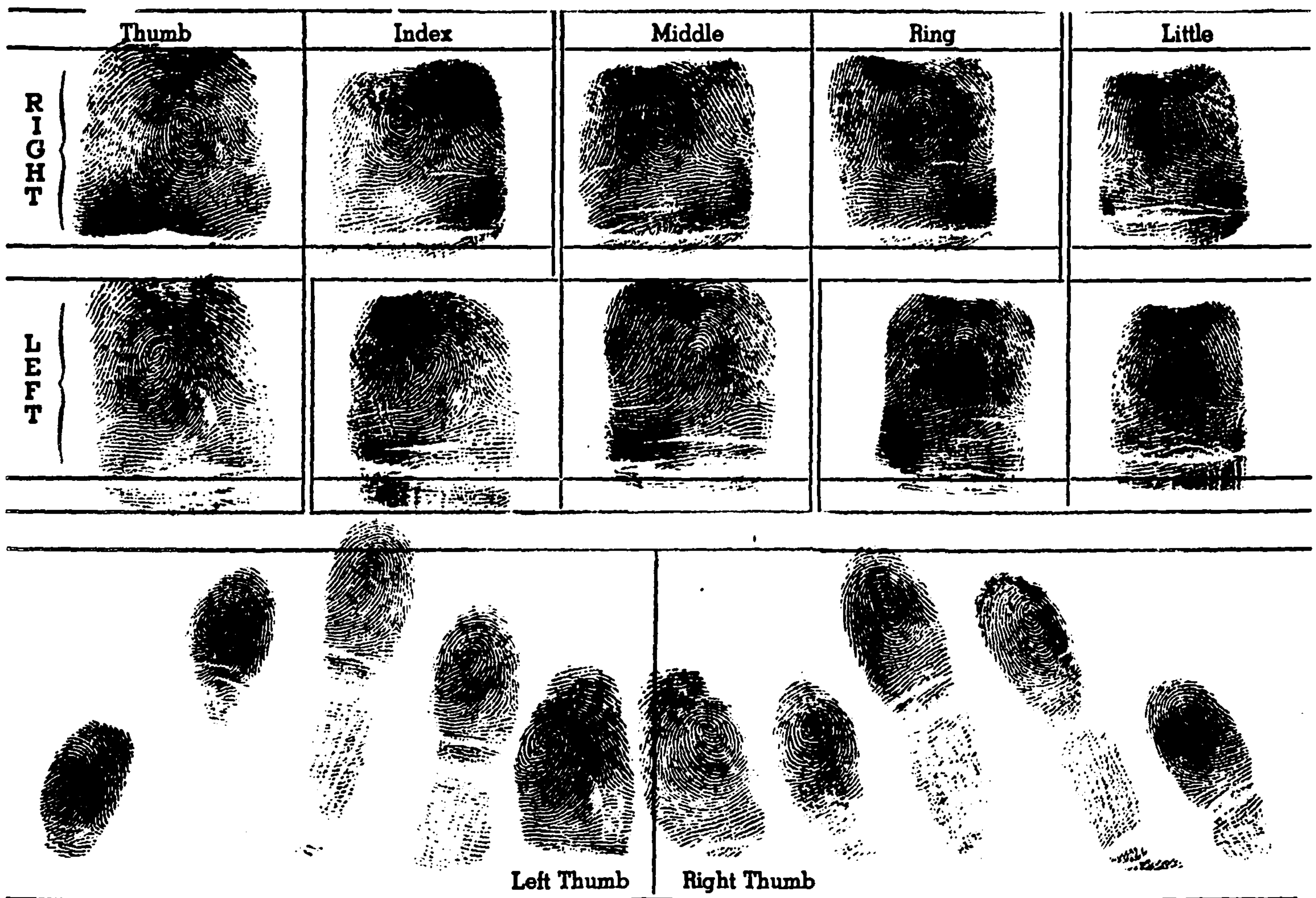


Figure 6 Inked Impressions

ROLLED PRINTS



DAB PRINTS

Figure 6 Inked Impressions

Figure 7 illustrates[6] the difference between an inked impression and a latent impression. Figures 8 and 9 show typical latent developed fingerprints[6].

An important point is that scene-of-crime impressions almost always yield only one or two fingerprints, usually of poor-to-bad quality. The Henry system, being a ten-finger system, is thus hopelessly inadequate for classifying single prints.

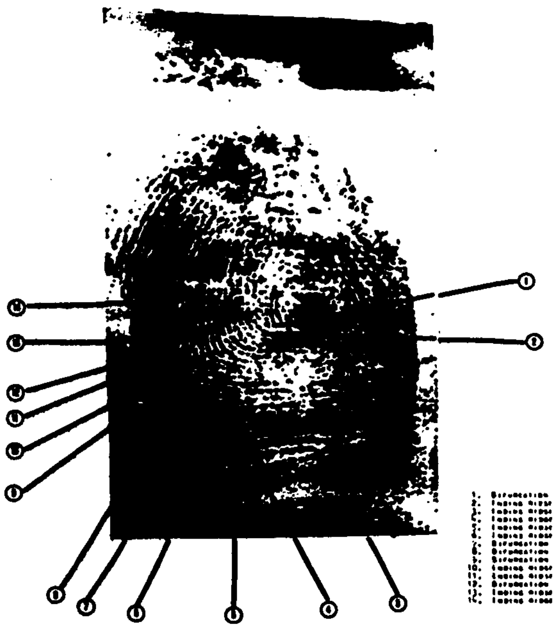
Single prints are sometimes classified by the 'Battley' system, which depends on minutiae but is in general not supported by large files of single prints. Thus, many criminals may owe their liberty to the fact that the present fingerprint system cannot effectively cope with scene-of-crime impressions.

A machine-oriented ~~classification~~ scheme that deals with single-fingerprint identification methods would seem to be indicated. Because of the memory available on today's machines, the speed of positive identification of a single print would more than make up for the small extra space needed to cross reference all prints of one person.

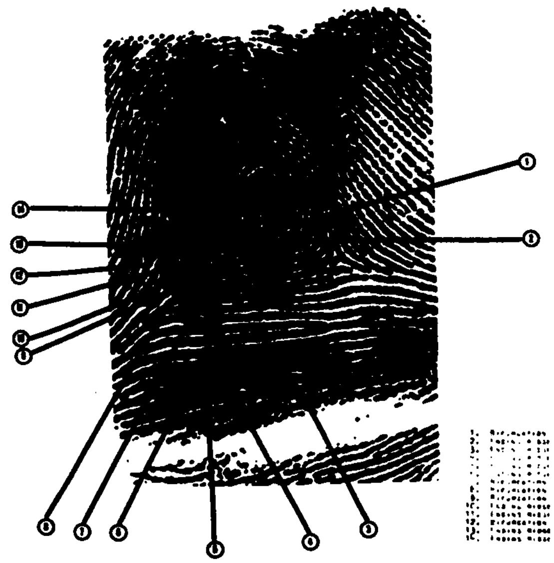
A third point in this enumeration of problems inherent in the Henry system is that manual classification is highly dependent on the temperament and experience of the fingerprint technician. Figure 10 illustrates how two technicians might classify the same fingerprints[6].

It is apparent that identification search time could be shortened and human error eliminated if automatic fingerprint-grokking could be used. A method applicable to single fingerprints would be more desirable than one based on ten fingerprints. Man-machine systems as well as pure machine systems should be investigated.

The work already done in automatic fingerprint-grokking is described in Chapter IV.

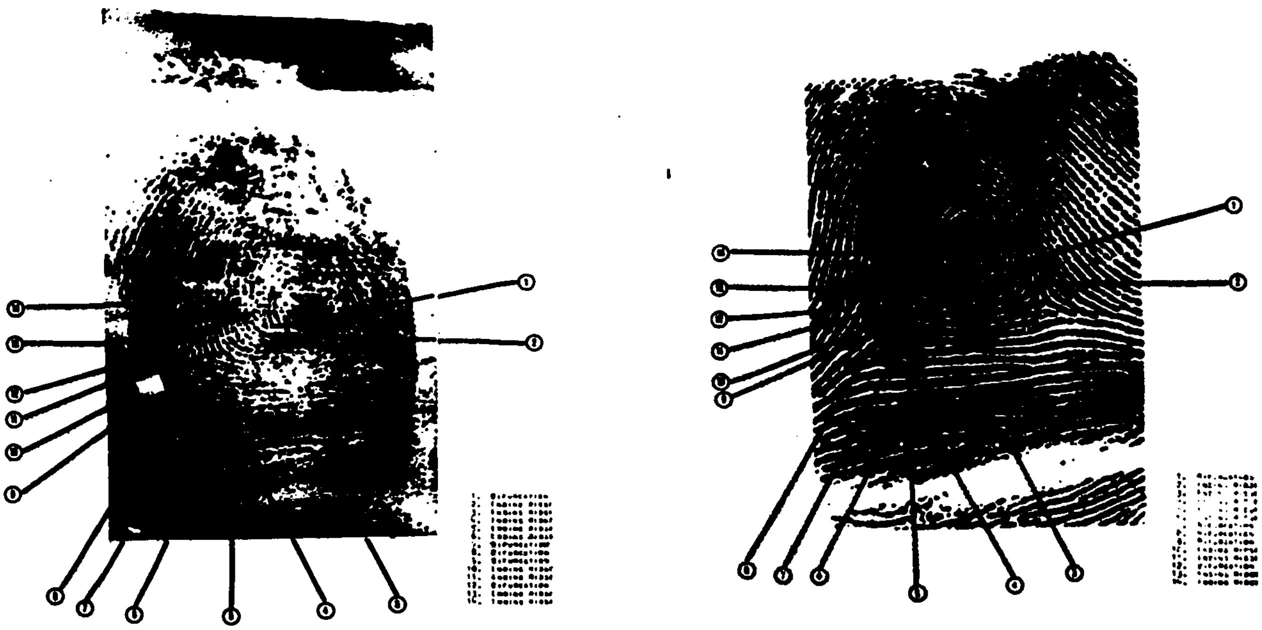


LATENT FINGERPRINT
7a



INKED FINGERPRINT
7b

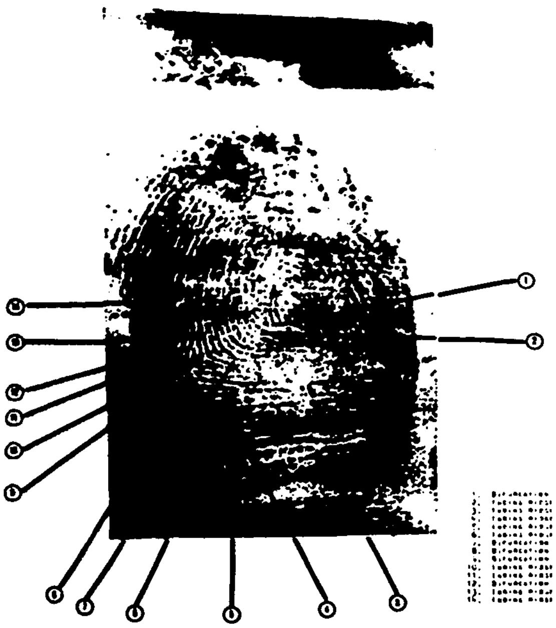
Figure 7 Comparison of a Latent Fingerprint with an Inked Fingerprint[6]



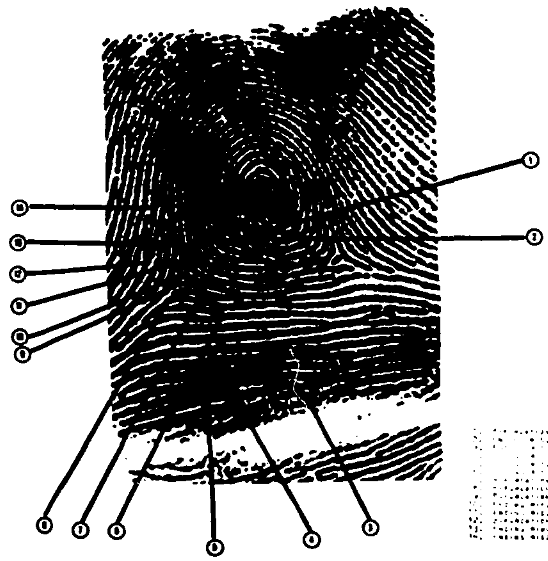
LATENT FINGERPRINT
7a

INKED FINGERPRINT
7b

Figure 7 Comparison of a Latent Fingerprint with an Inked Fingerprint[6]



LATENT FINGERPRINT
7a



INKED FINGERPRINT
7b

Figure 7 Comparison of a Latent Fingerprint with an Inked Fingerprint[6]

Figure 8 Typical Latent Fingerprints[6]

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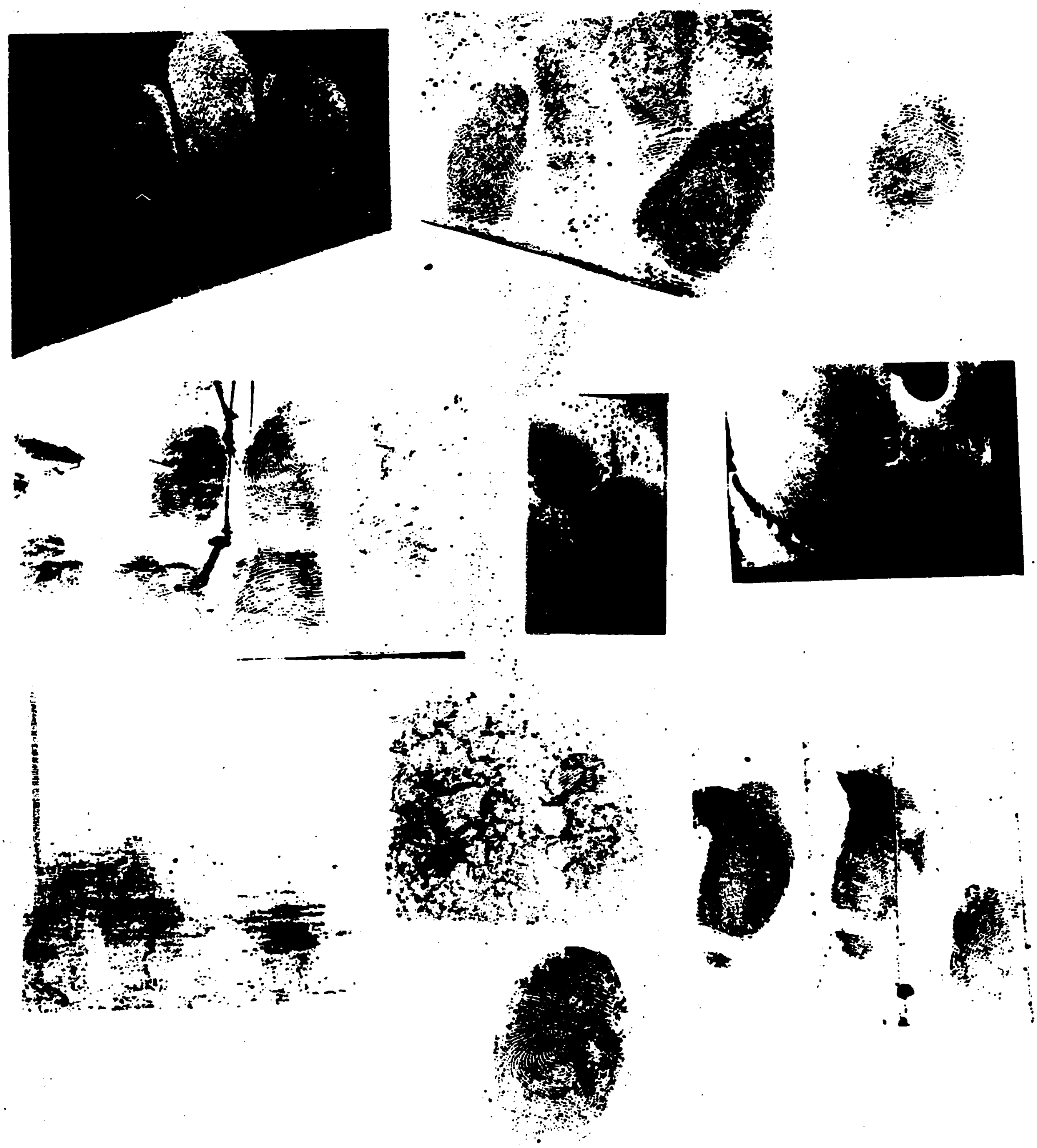


Figure 9 Typical Latent Fingerprints[6]

Figure 9 Typical Latent Fingerprints[6]

Plain Loop or Central Pocket Loop

10a

Plain Loop or Central Pocket Loop

10b

Plain Loop or Tented Arch

10c

Double Loop or Central Pocket Loop

10d

Double Loop or Plain Whorl

10e

Plain Loop or Accidental

10f

Figure 10 Fingerprints with Two Possible Classifications[6]

CHAPTER IV

AUTOMATIC CLASSIFICATION METHODS

4.1 Input Methods

Since the fingerprint is in some way to be analysed by a computer, let us first consider the problems of feeding a fingerprint into a computer. It is assumed that the whole image is required so that selective parts or the totality can be processed at will.

In most of the following methods, an optical scanning input technique is used. This is perhaps the fastest for inputting the whole fingerprint image. All the authors are, however, vague about how the original image is inputted into the machine. All methods, it seems, provide for getting the image into the machine but their authors present only the operations performed on the image once it is in the machine. The reasons for certain input mechanisms are not explained, and the use of different scanning techniques for inputting the image is discussed in only a few of the cases.

4.2 Problems in Optical Systems

An optical input device may appear as in Figure 11. In this input subsystem, it is assumed that:

(1) The light source is capable of putting out an essentially collimated beam of light.

(2) The image contains distinct boundaries, as well as high colour (black - white) contrast.

(3) The photomultiplier reaches steady state quickly.

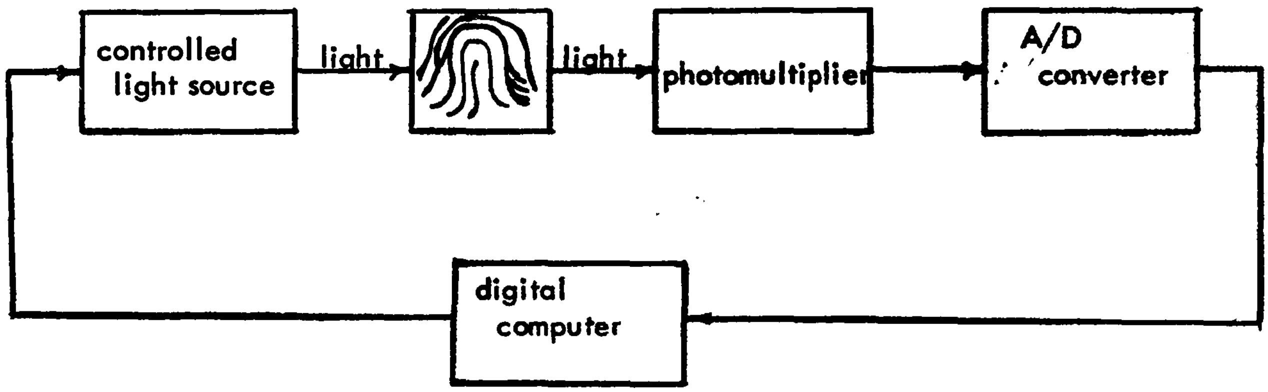


Figure 11 A Typical Optical Input System

The reasons for these assumptions may be tabulated as follows.

(1) Consider that the light source is somehow to be digitally incremented across the picture to be processed. First of all, if the beam is totally uncollimated and the optical distance between the photomultiplier and light source is large, then the dispersion of the light will take in more of the image than is desirable. These conditions will not yield information about a point on the picture, but about a finite 'smear'. For information about points - not smears - a narrow beam of light is indicated. If the beam of light is wider than the digital increment provided by the computer, then information about two consecutive points will overlap, which may not be desirable. If the increment is too large, small details essential to the processing may not be recorded.

(2) The picture medium - film, drawing paper, etc. - should also be considered when figuring the light dispersion that can be tolerated. If the code to be used by the computer is a black-white code (0-1), it is essential that the blacks be as black as possible and the whites be as transparent as possible, so as to generate a high-contrast machine

image. Without a high-contrast picture, black and white can easily be merged. With an eight-level gray code, high-contrast pictures are critical since the separation between black and white must be such that the grays can be easily classified.

(3) The photomultiplier has to rise to steady state rapidly so that the input operation can go fast. It is also assumed that a blanking pulse during incrementation is used so that the photomultiplier does not have to settle down from the light collected in transit from one point to another.

It will be worthwhile to look into the problems associated with fingerprint images a little more deeply since problems associated with the other pieces of equipment can usually be kept within tolerable limits by knob-twisting or, in the extreme, by replacing or redesigning the equipment.

Figures 12 to 16 illustrate[32] the various fingerprint types, taken under the best of working conditions. First of all, it can be seen that whether compared within a print or between the prints, the dark areas are not uniformly black, nor are the light areas uniformly white. Also, many of the prints are smudged and blurred. The important point is that these defects, which amount to errors of exclusion or inclusion, are easily filtered out as a matter of judgment by the human technician, whereas the machine has a hard time of trying to determine how black, black is.

Figure 17 is a reprint of a photograph of a fingerprint[28]. There is a smudge in the upper righthand section of the figure. If the machine had determined a standard black by the first scan, then scanning through a lighter or a darker black area would foul up the machine's sense of absolute blackness and lead to spurious data-recording. To make a cogent recording of the picture, the machine would need a sense of relative

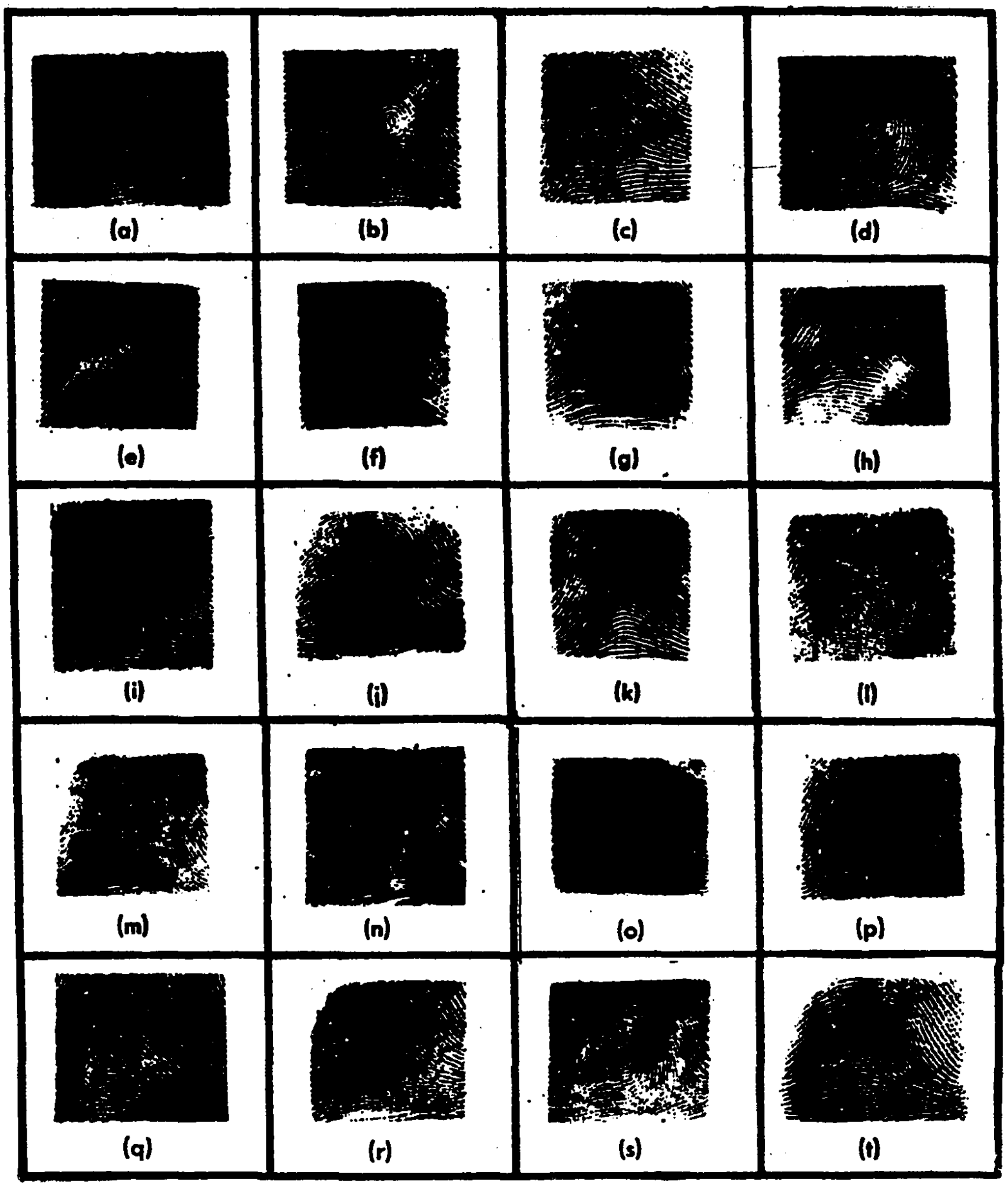


Figure 12 Central Pocket Loops[32]

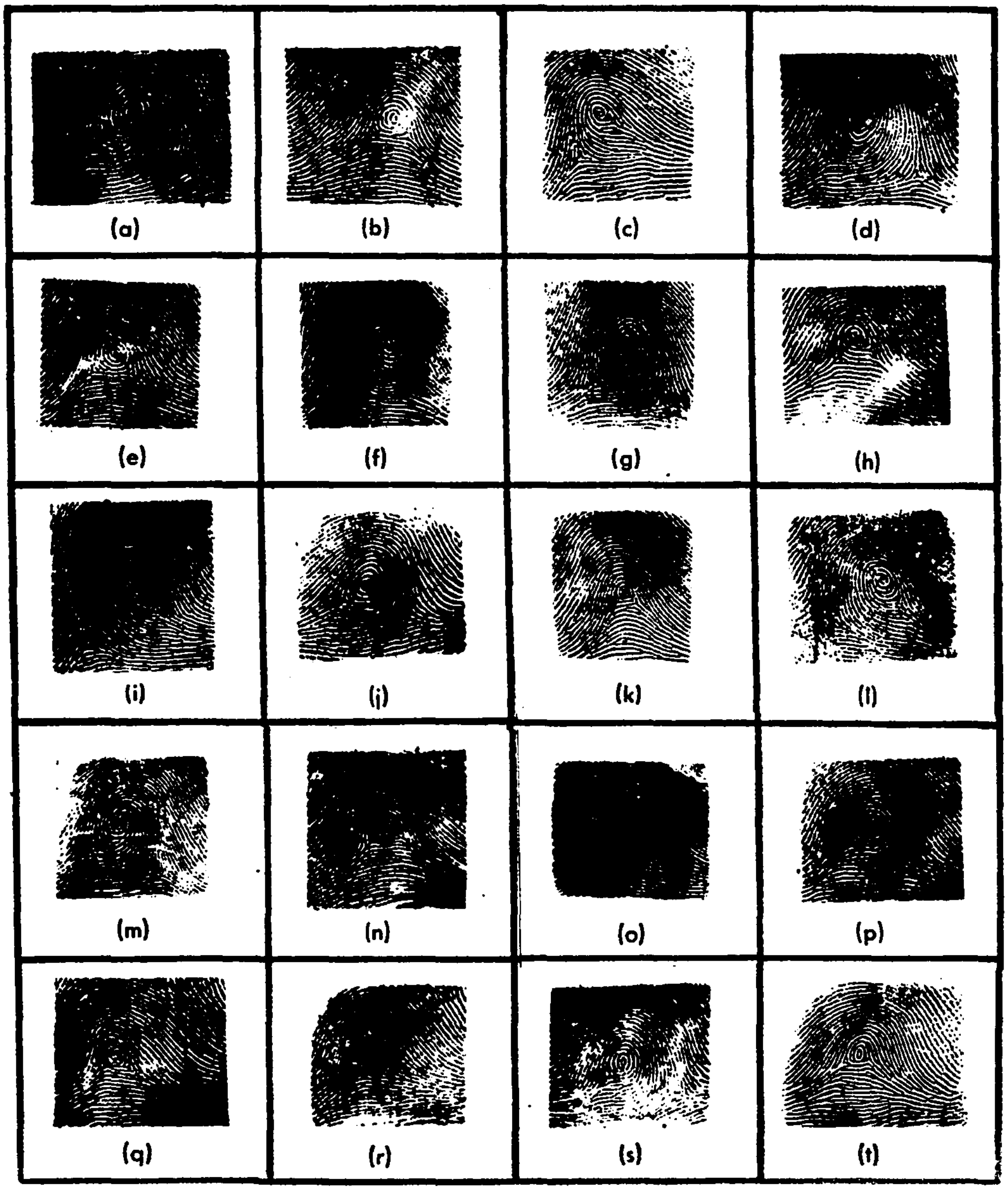


Figure 12 Central Pocket Loops[32]

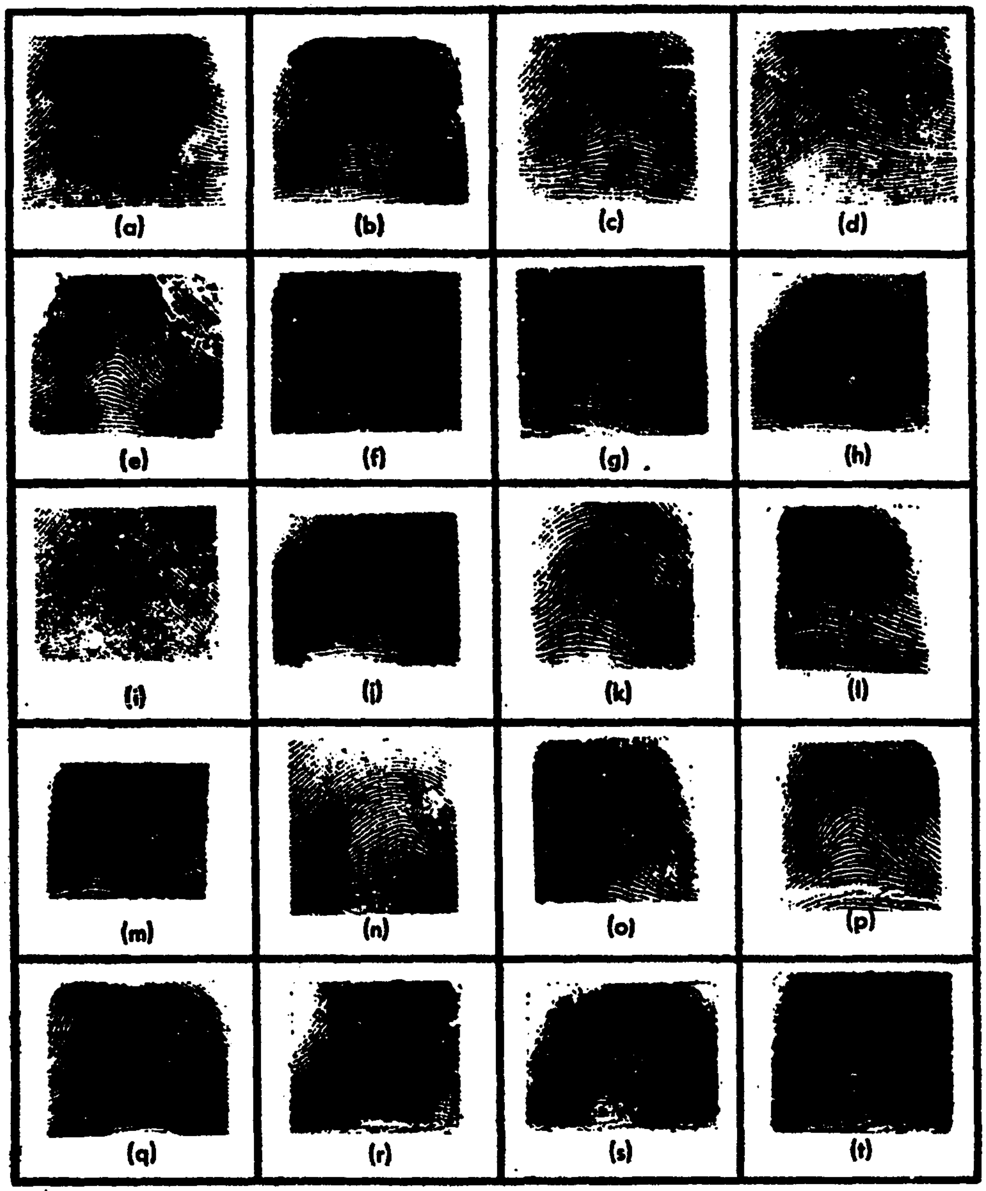


Figure 13 Arches[32]

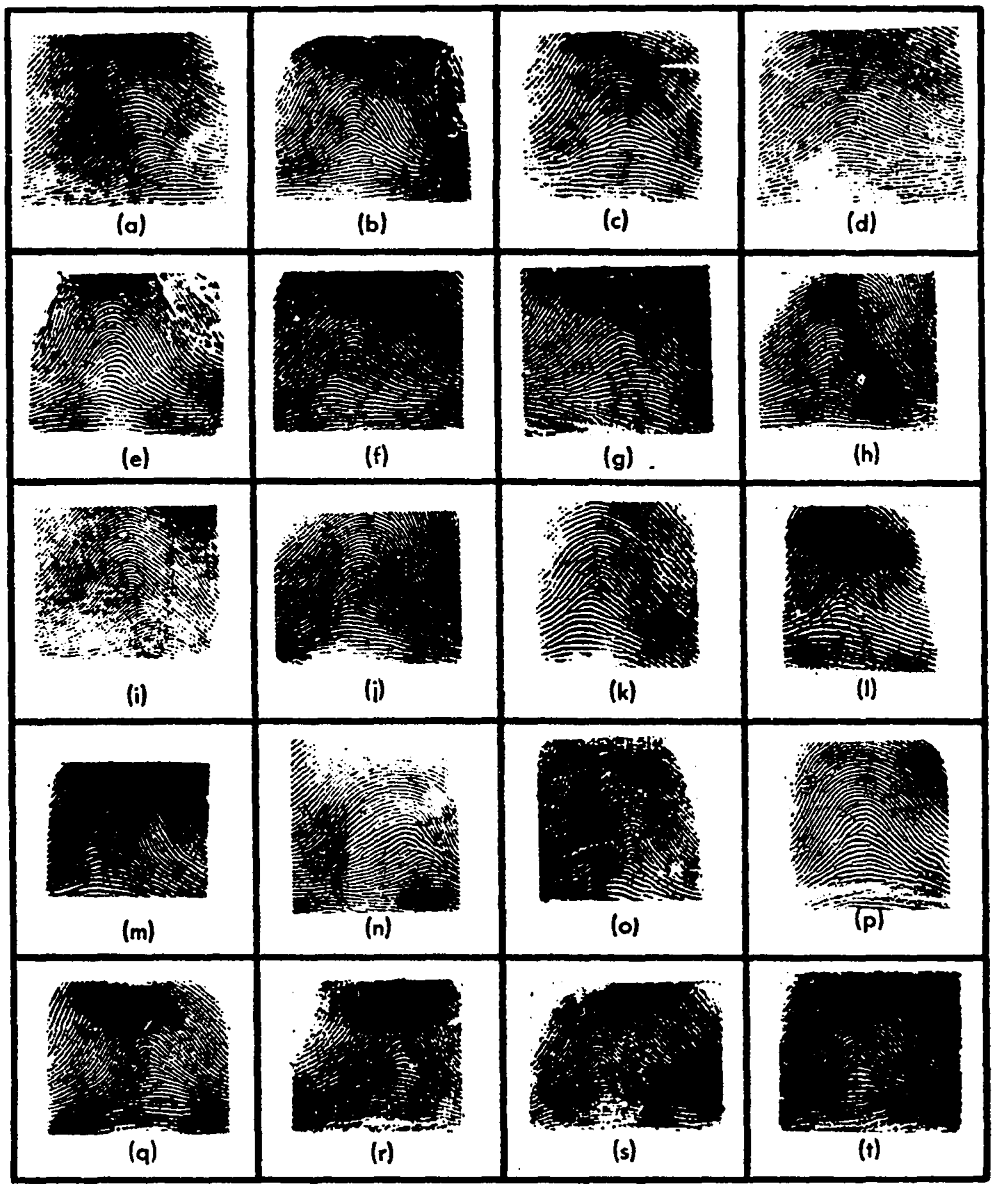


Figure 13 Arches[32]

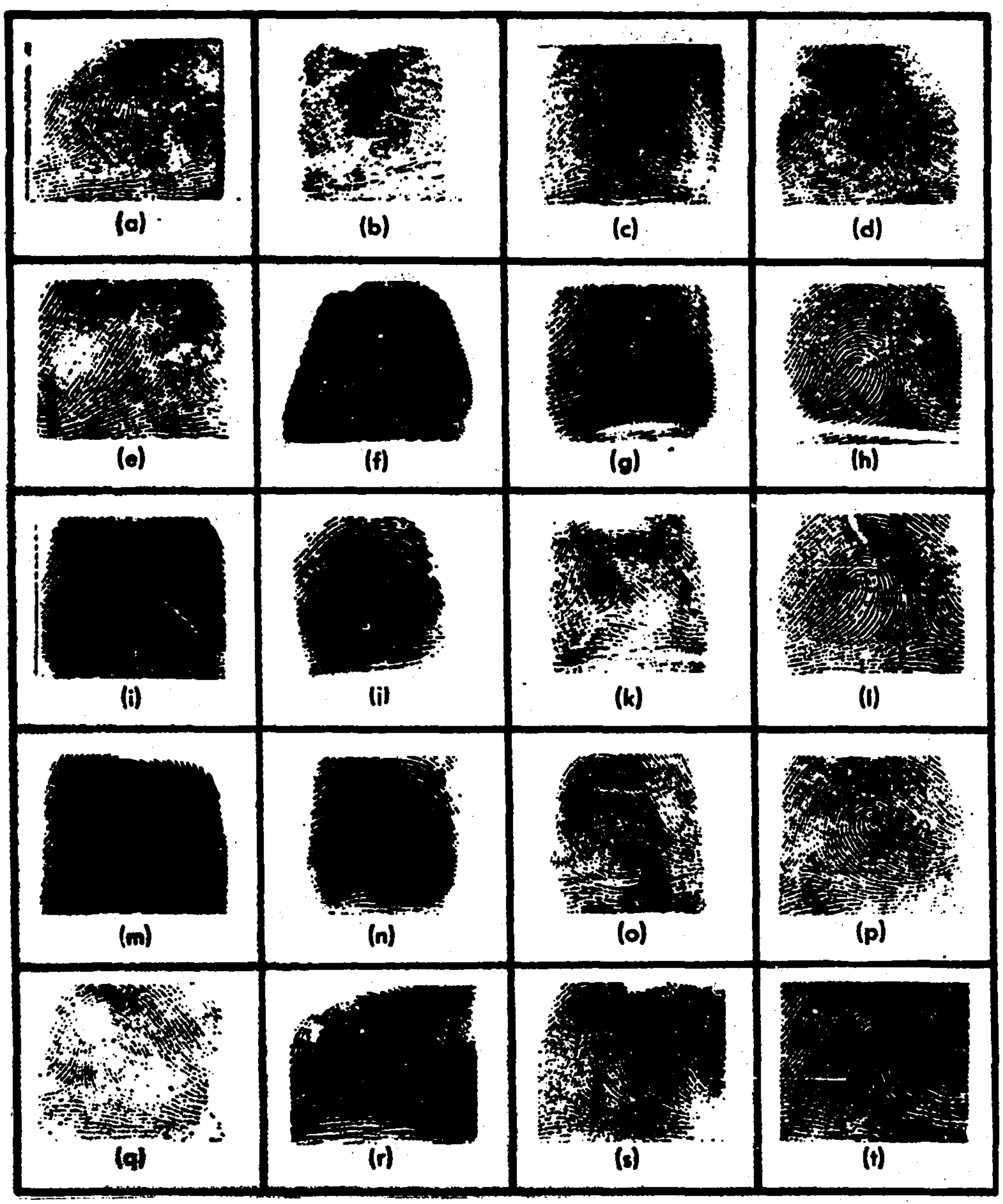


Figure 14 Radial and Ulnar Loops[32]
(Right hand)

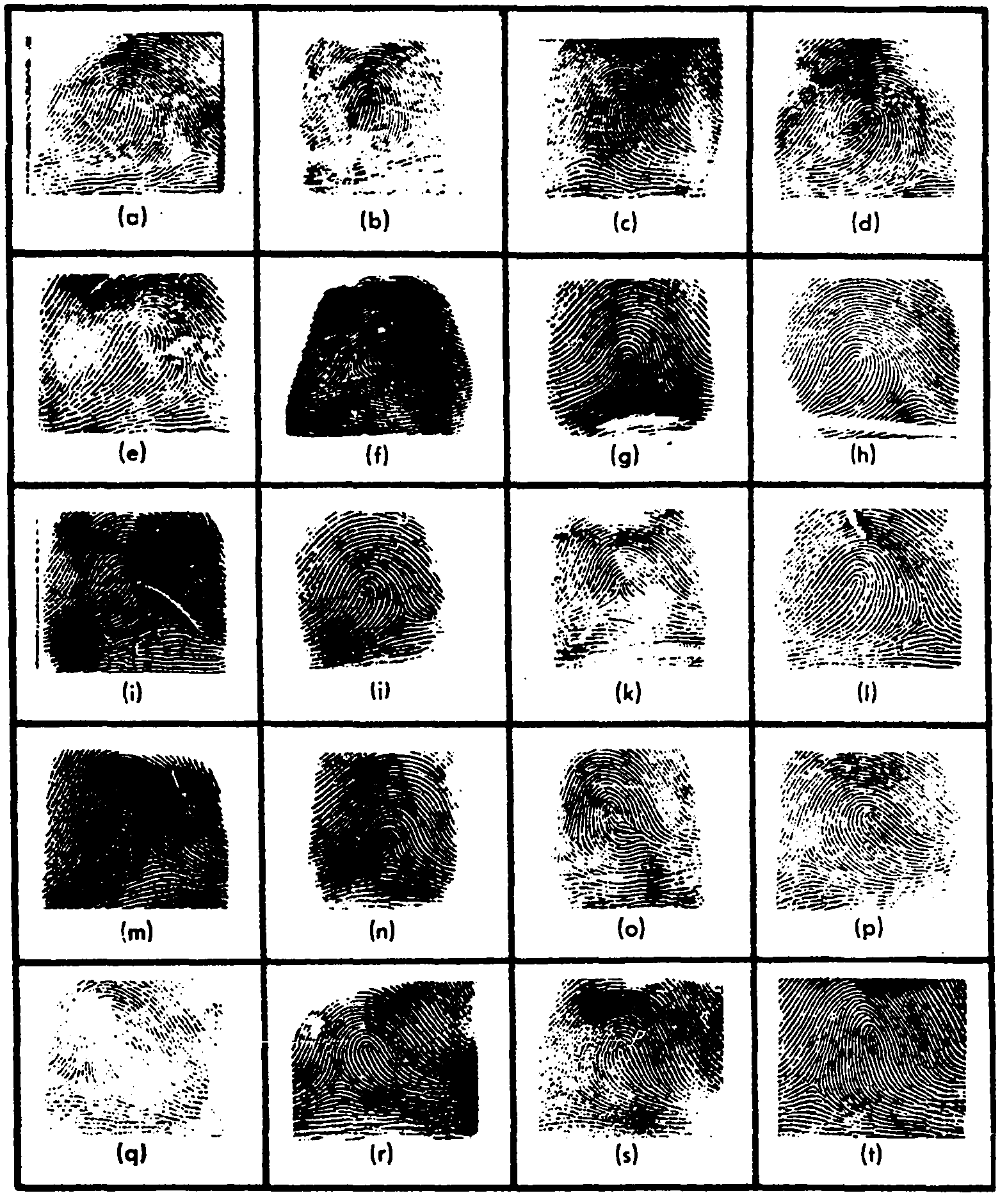


Figure 14 Radial and Ulnar Loops[32]
(Right hand)

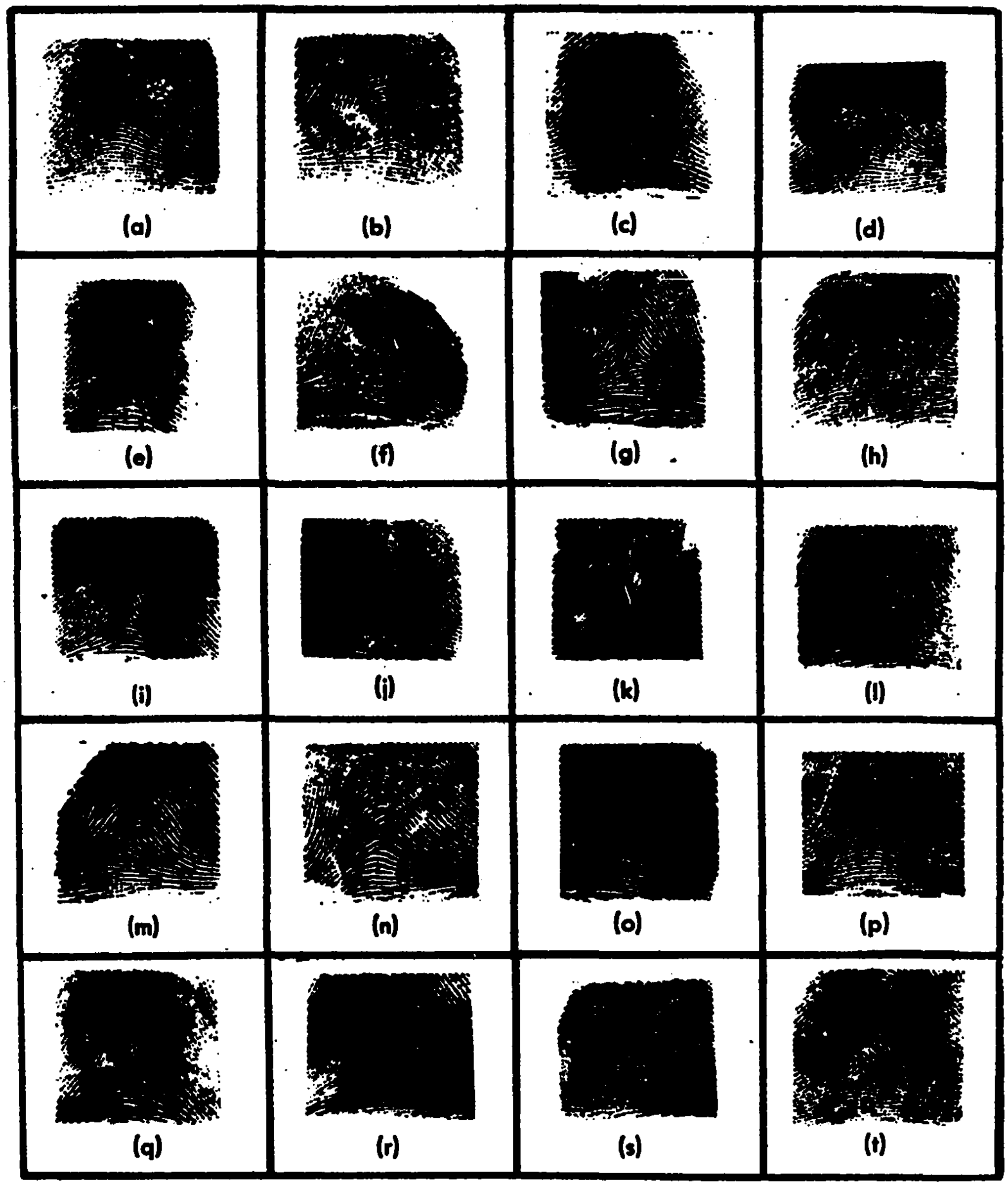


Figure 15 Tented Arches[32]

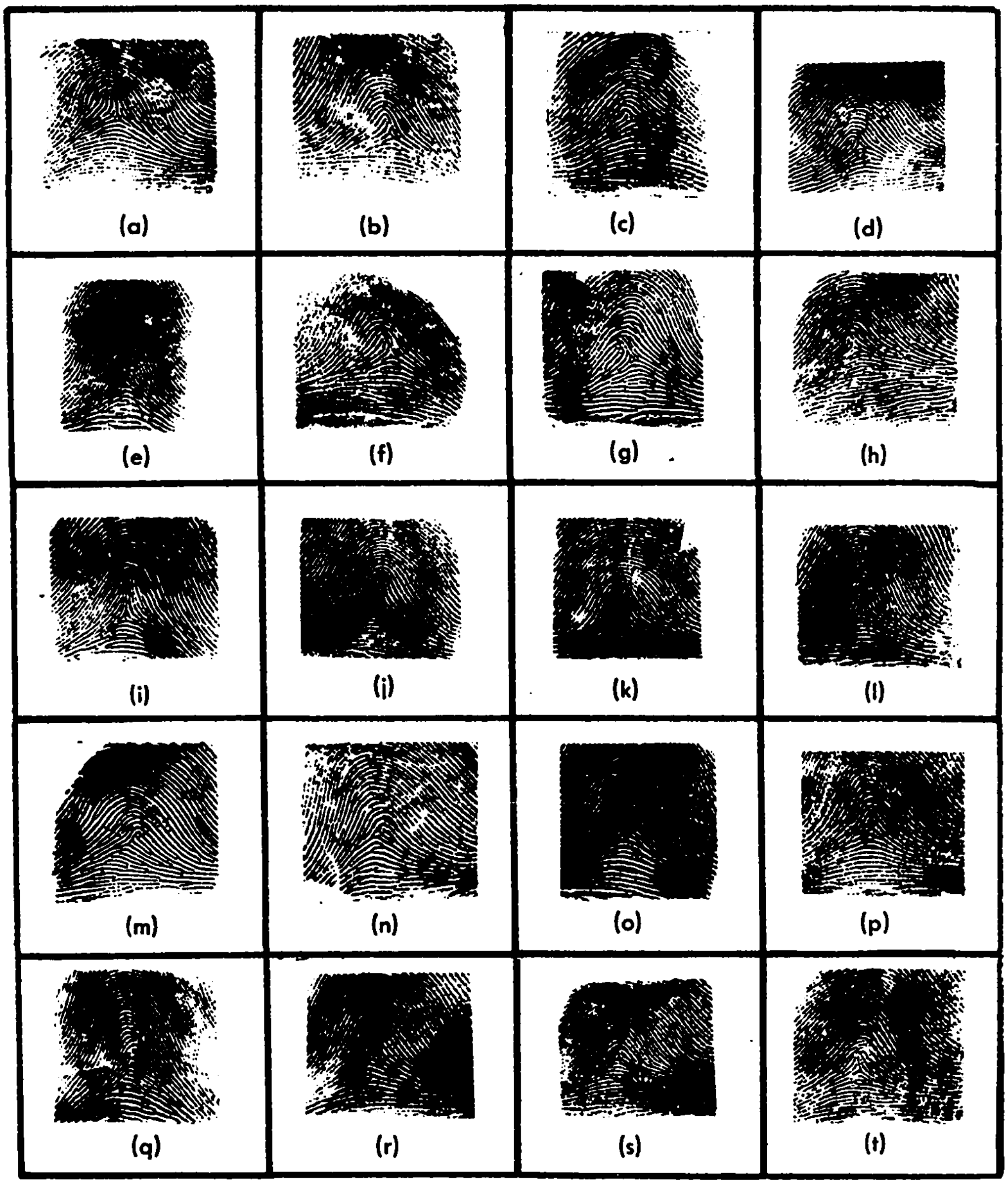


Figure 15 Tented Arches[32]

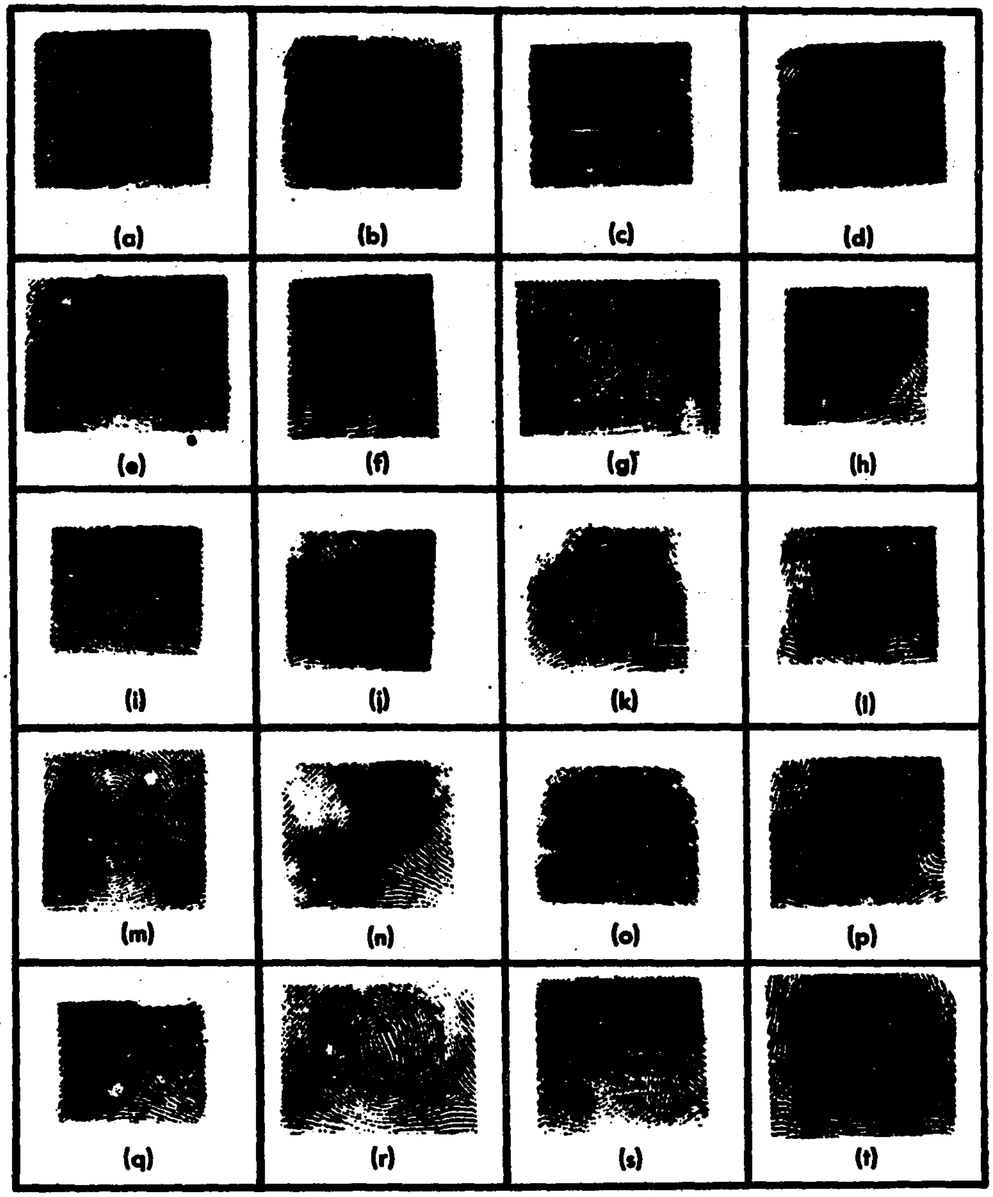


Figure 16 Whorls[32]

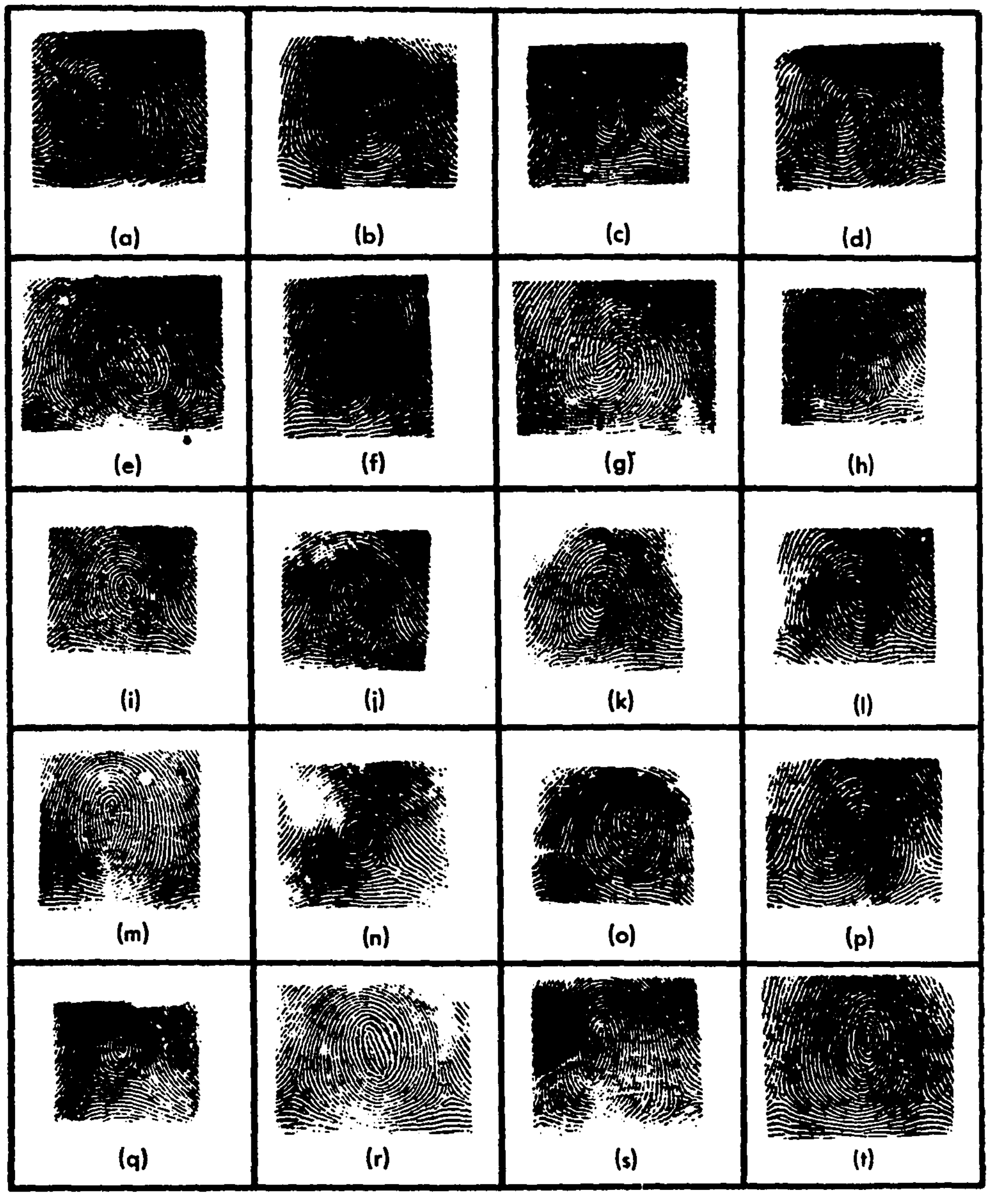


Figure 16 Whorls[32]

Figure 17 Fingerprint Enlargement[28] (8.5 to 1)

blackness. This 'sense' could be supplied by neighbourhood operations using some type of averaging or weighting, but it must be remembered that every extra operation takes up valuable time.

Briefly, the main problem with fingerprint images is their nonuniformity in terms of inking density. The machine has to be told explicitly how to interpret nonuniformities that a human technician filters out automatically.

4.3 Automatic Classifications

There are basically two broad categories of automatic fingerprint classification. The first encompasses those methods that require the recognition of ridge characteristics and derivation of a mathematical algorithm of some sort to express the location and relationship amongst those characteristics. The second includes those methods that treat the whole image by such techniques as ridge-tracing or secondary pattern development by diffraction processes.

4.3.1 Category I

4.3.1.1 The NYSIIS Fingerprint Classification and Identification System

The fundamental tenet of the New York State Identification and Intelligence System (NYSIIS)[6] method is the same as in all current systems: the final identification of a fingerprint depends on the location and structure of the minutiae, the minute ridge characteristics. The rationale is that this level of detail has proved satisfactory in establishing the uniqueness of individual prints on a manual/visual basis and should therefore be capable of doing the same on an automated/electronic basis. This choice of characterization scheme resulted by elimination from the following quoted list:[7]

(1) Use a revised scheme based on current classification schemes.

(2) Use minute characteristics in a single fingerprint.

(3) Use pore structure data in a specified area of the print.

(4) Use chemical composition of pore secretions.

(5) Use a gestalt or whole-image process.

The first choice in this list is an example of the 'Tourist' syndrome. Choice 3 is an excellent example of the 'Forest-for-the-Trees' syndrome.

The NYSIIS method optically enlarges the fingerprint on a special screen. The coordinates of all minutiae are indicated by a technician using a light pen. The core and delta are also located. Next, the picture is scanned and all the minutiae are recorded in the machine. Finally, the positions of the minutiae are referred to the core-delta reference axis, a line between the core and delta. Figure 18 illustrates[6] the core-delta reference system, and Figure 19 shows the identified minutiae used[6].

4.3.1.2 Comments

(1) A man-machine interface (Rand tablet and light pens) has been mentioned. Although not totally automatic, the man-machine exchange may provide a better classification system than one that depends only on man or machine.

(2) The location of the minutiae are determined by coordinates, but a fixed-axis reference scheme may be hard to implement on a computer. In fact, NYSIIS[6] reports:

> One of the leading problems for most 'automated' systems is that of establishing precise pattern orientation with a high degree of consistency time after time. Theoretically, this seems quite easy to do. In practice, is altogether a different story. It is not only one of the leading problems, it is one of the most difficult to solve.

NYSIIS seems to solve this problem by circumventing it. A relative fixed axis is

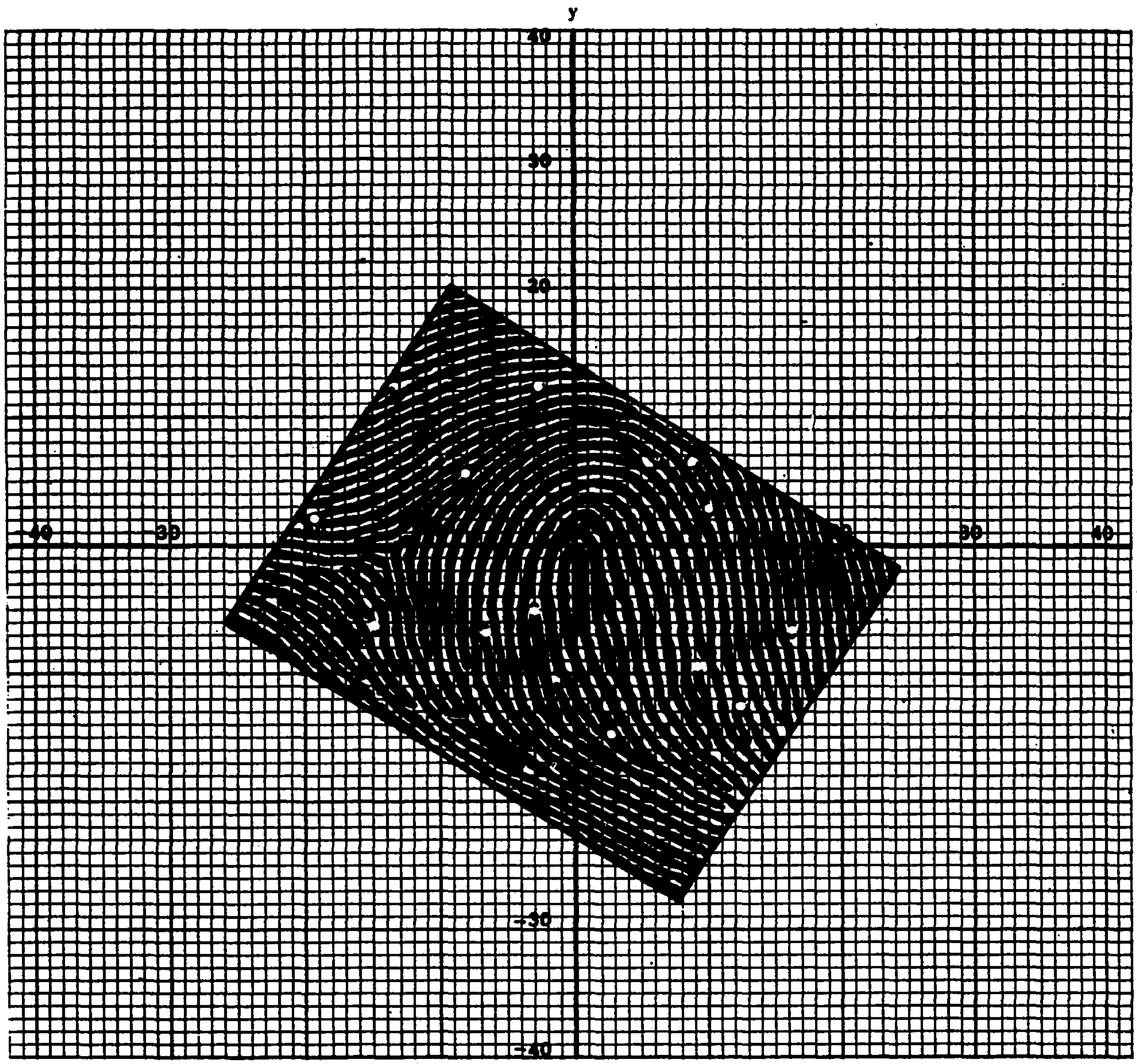


Figure 18 Core-Delta Coordinate System

A cartesian coordinate system with the origin at the core of the fingerprint and the -x axis passing through the delta[6]

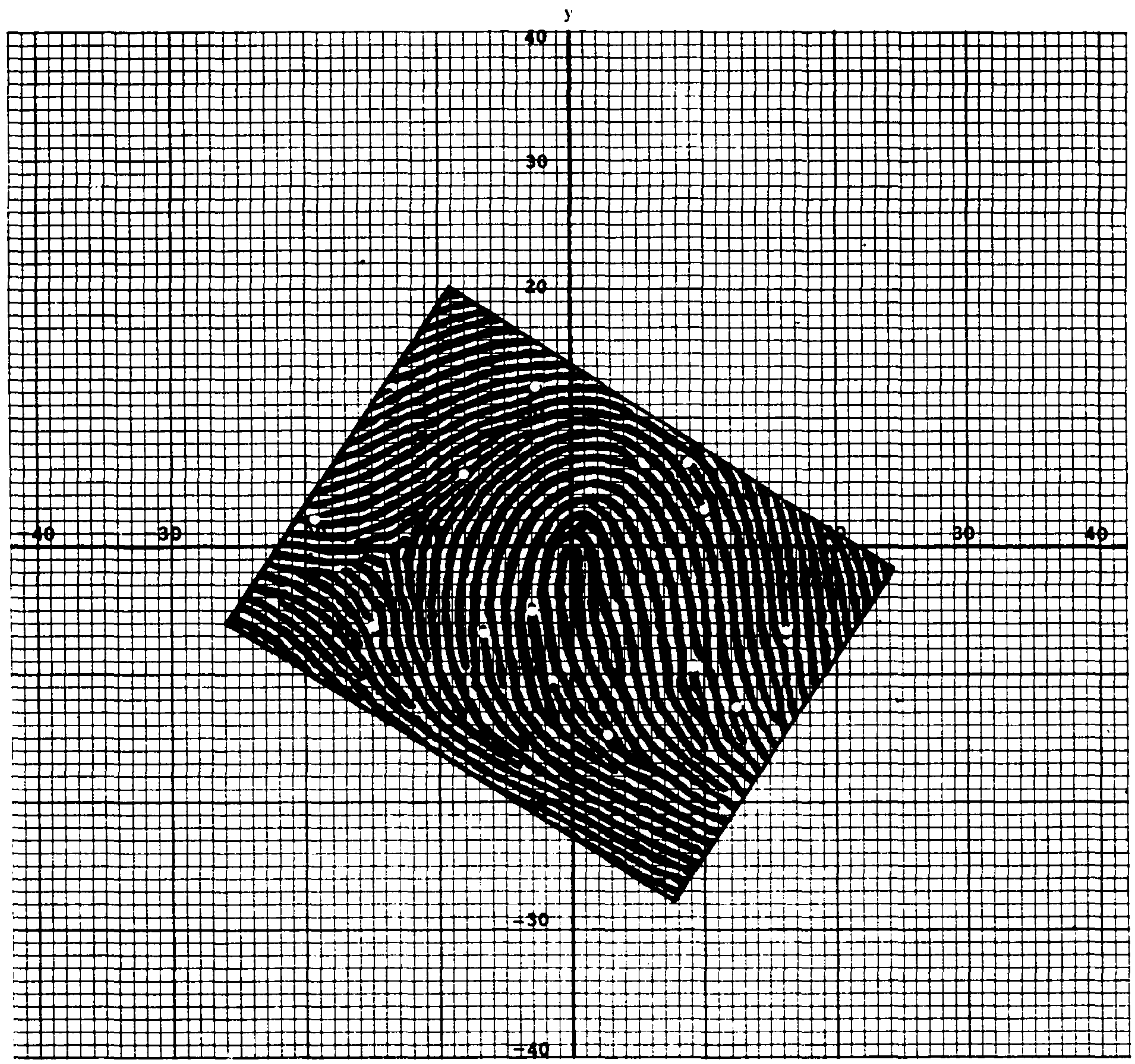


Figure 18 Core-Delta Coordinate System

A cartesian coordinate system with the origin at the core of the fingerprint and the -x axis passing through the delta[6]

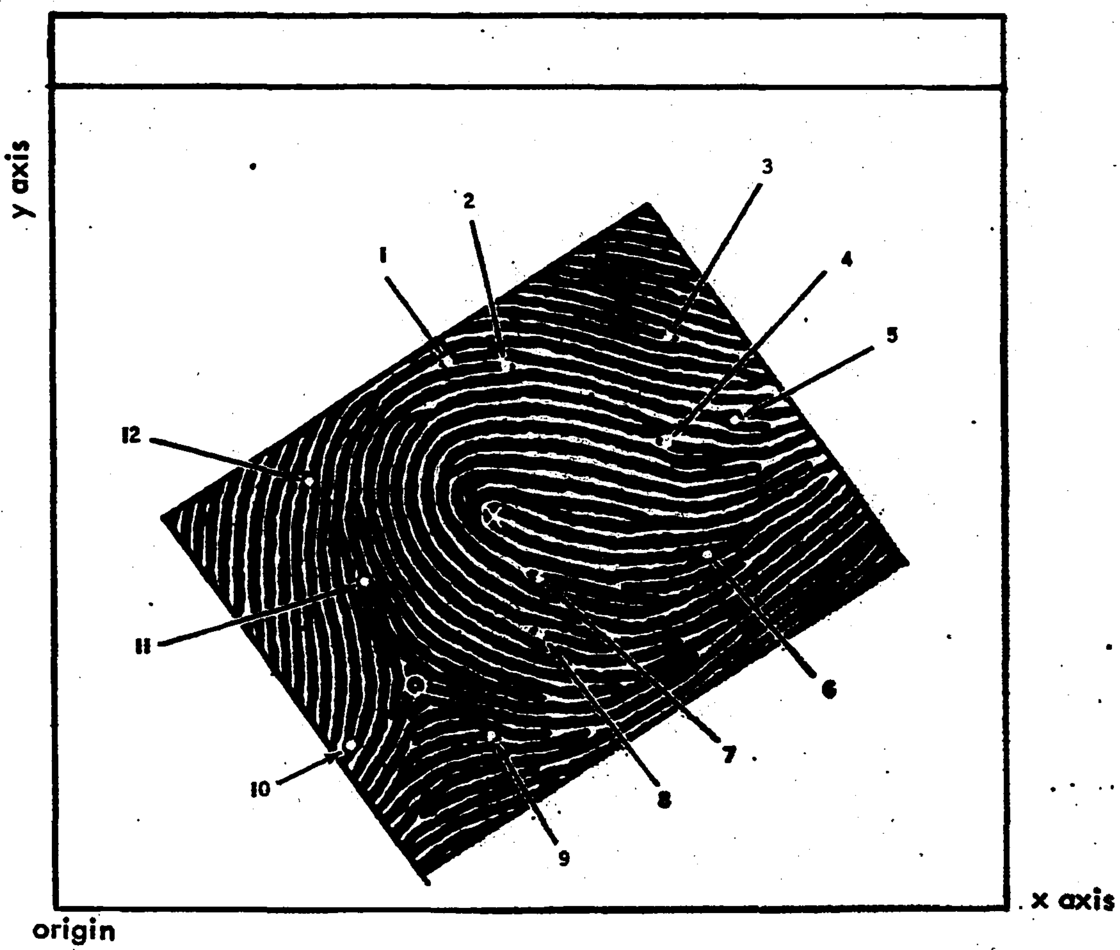


Figure 19 Identified Minutiae[6]

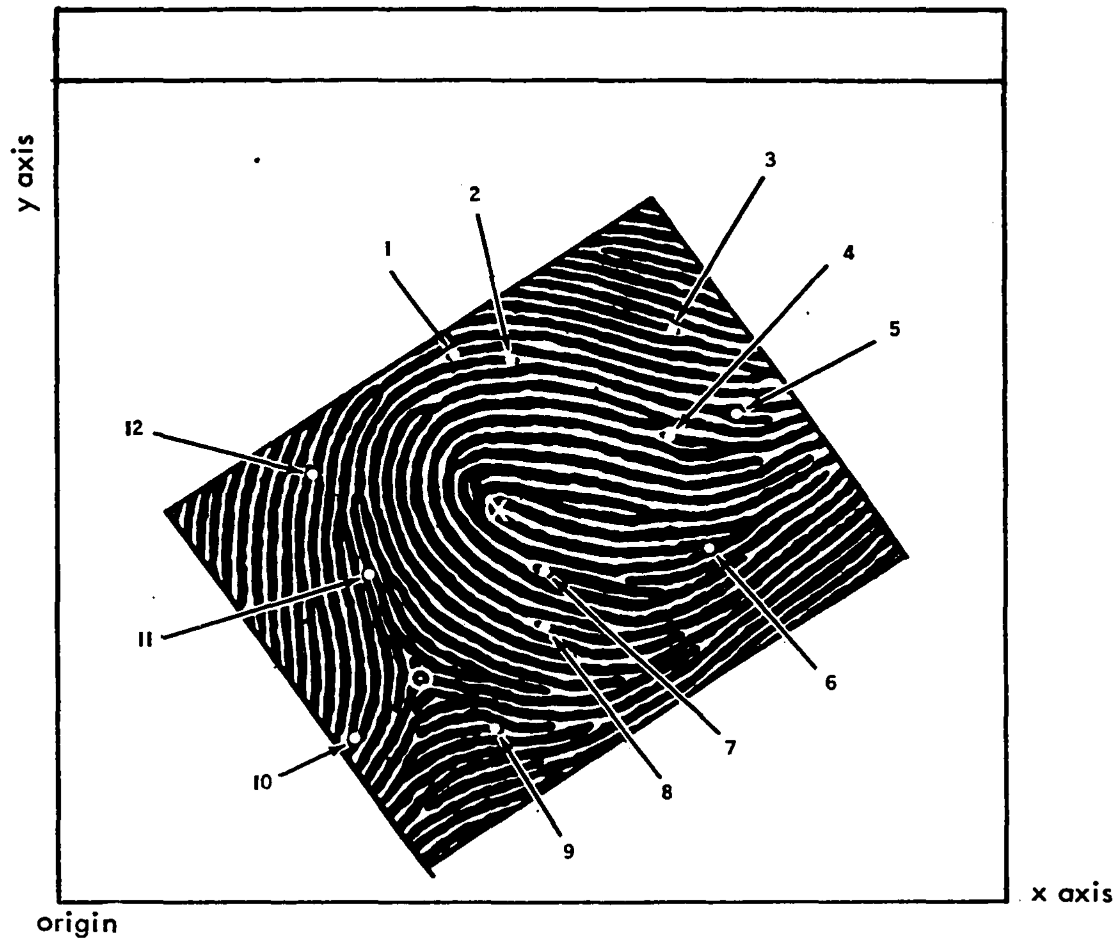


Figure 19 Identified Minutiae[6]

defined, but since it is defined by a human technician there is room for error.

Of the several problems inherent in NYSIIS, the most important is that all of the minutiae needed for classification are assumed readily available.

Figure 19[6] presents an idealized fingerprint with some preidentified minutiae[6]. Figure 20[6] shows the same fingerprint with other minutiae identified. These minutiae were either disregarded or overlooked by the NYSIIS classifier. This brings up the question, which minutiae should be chosen?

Using all the minutiae may prove inconvenient, but it is a delusion to assume that a technician can consistently choose enough different minutiae to make a positive identification. A solution would be to scan separately for different types of minutiae, but this may also take up more time and storage than it is worth.

The identification of minutiae is a nontrivial problem. Appendix B contains figures[32] that are good high-contrast enlargements of prints in which the circled areas indicate ridge characteristics that may be actual minutiae or may be noise.

Another problem is that fingerprint size is critically dependent on how much pressure is applied to produce the print. An algorithm dependent on distances that are nonconstant will not be able to identify large numbers of prints. If error limits are set on the distances, a group of prints rather than a single print will be identified, and the search time will be much longer.

The last, and perhaps most obvious of the notable problems is that provisions for identifying prints without a core or delta (such as an arch) do not exist.

Perhaps the only reason that the NYSIIS technique is semi-automatic is that the calculations required to convert to the core-delta system may be too tedious for the

Figure 20 Minutiae Unidentified[6] in Same Fingerprint as in Figure 19

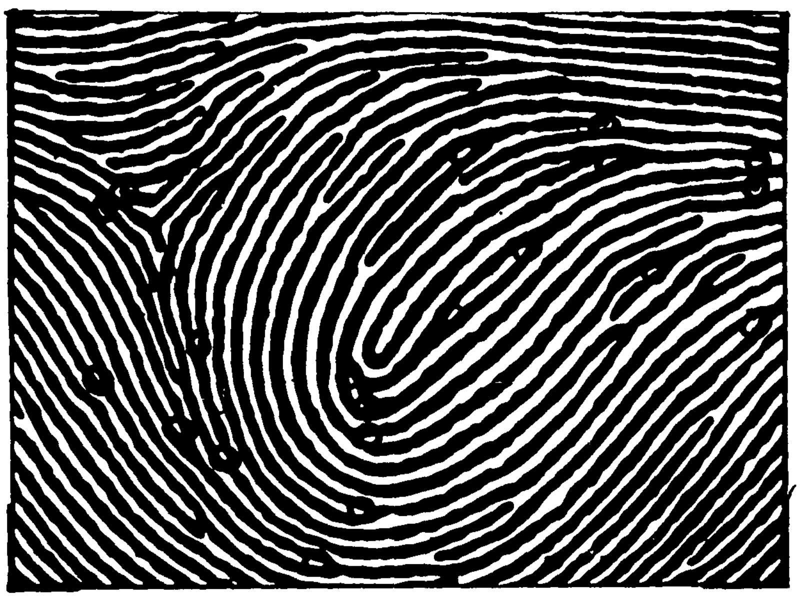


Figure 20 Minutiae Unidentified[6] in Same Fingerprint as in Figure 19

average fingerprint technician. The method should be looked upon as an algorithm based on a specific pattern rather than as a pattern-grokking technique based on an algorithm.

4.3.1.3 Advanced Computer-Based Fingerprint Automatic Classification Technique (FACT)

In essence, the FACT[37] system is the same as NYSIIS in that both locate and identify minutiae; however, FACT records all the minutiae according to the number of ridges between a given minutia and all others.

Figure 21 shows a typical print with the minutiae identified[37], and Figure 22 shows a table of interminutiae ridge counts[37]. A problem evident here is that of correctly orienting the print so that a certain minutia is always number 00. If this orientation were not ensured, the permutation tables generated by the system in order to match a classification print to an identification file would be excessive.

Since most of the information pertaining to FACT is of a proprietary nature, only vague generalities can be discussed. For example, it is mentioned that FACT could use a flying-spot scanner, searching helically or circularly to identify the minutiae. There is also some mention of a scan method that would be useful for extracting minutiae information - except that success of the method, like that of many another, patently depends on simplicity of the fingerprint, an assumption not corroborated in nature.

In FACT, three circular scans are made about each point of a rectangular grid defined on the print, the grid being obtained by x, y increments of the scanner. As the circular scan is made, all intersections of the circle with the print are recorded as indicated in Figures 23 and 24[37].

This technique has two facts against it. The first is that ridges are never as

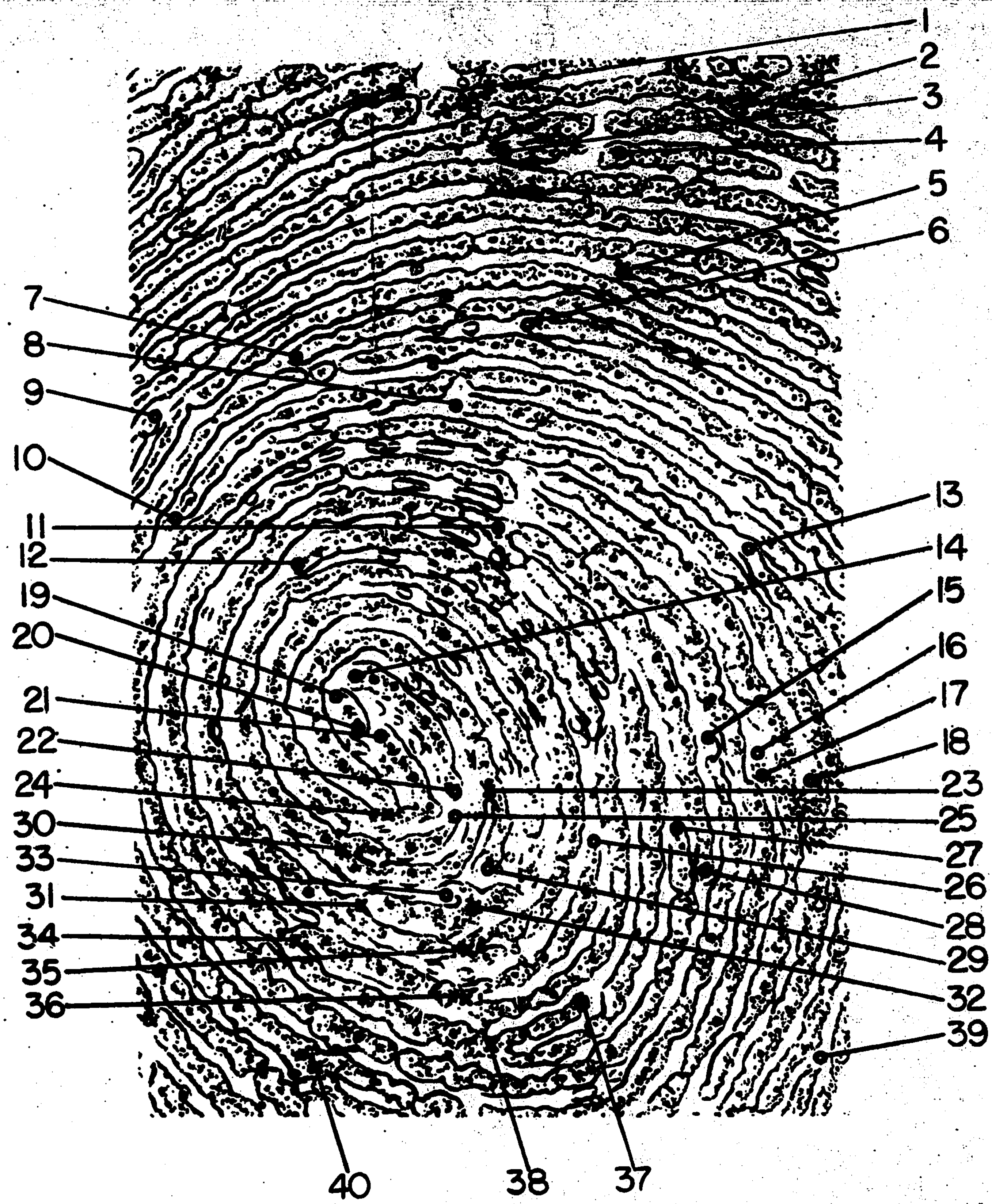


Figure 21 Actual Fingerprint Identifying Some Minutiae[37]

Figure 21   Actual Fingerprint Identifying Some Minutiae[37]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40		
1		1	2	1	5	7	4	7	11	11	11	15	14	13	13	12	15	15	16	16	14	17	17	16	16	15	16	20	20	17	19	21	17	19	18	21	18	21	19	24	1	B
2			1	1	5	7	4	10	6	10	13	14	12	19	15	15	15	14	19	20	19	19	20	23	21	17	16	16	20	23	24	21	21	25	22	23	19	20	16	27	2	E
3				0	3	5	4	7	3	6	10	10	9	13	12	11	11	10	14	15	16	15	14	17	16	15	13	12	16	17	18	17	16	19	18	19	17	19	16	25	3	E
4					3	5	4	7	4	7	11	10	10	15	13	12	12	12	16	18	17	16	17	18	17	15	14	12	17	22	20	18	19	24	19	19	16	21	15	25	4	E
5						2	1	5	4	5	8	9	6	13	9	6	6	7	14	14	14	15	16	15	19	11	16	9	14	15	19	15	13	18	16	17	13	10	12	21	5	E
6							0	2	2	3	5	6	3	10	6	6	5	11	11	11	11	10	9	14	11	9	8	7	10	14	14	11	12	16	12	13	12	13	12	20	6	E
7								2	1	1	4	5	3	8	6	7	7	6	8	8	9	8	7	11	9	7	7	8	10	10	11	11	11	11	12	14	12	13	14	15	7	E
8									3	2	3	3	1	7	3	3	3	4	8	8	3	7	7	9	8	6	5	5	9	11	12	8	10	13	9	10	8	10	11	17	8	E
9										2	5	6	8	9	11	13	13	15	9	9	10	10	11	9	10	12	12	14	12	9	10	13	12	9	14	13	17	18	20	12	9	E
10											5	3	8	6	10	11	11	12	6	6	7	7	7	5	7	10	10	12	10	6	6	9	9	8	11	11	14	13	19	8	10	E
11												1	3	5	2	2	3	3	6	5	5	4	4	6	4	3	2	2	5	7	8	6	5	9	6	7	6	8	7	12	11	B
12													6	3	6	7	7	8	3	3	4	4	4	4	4	6	6	8	6	4	5	7	8	9	9	9	11	12	14	9	12	E
13														9	3	2	2	1	10	10	10	9	8	11	8	6	4	4	7	12	11	7	8	12	8	8	6	8	4	12	13	E
14															6	8	8	9	0	0	0	0	0	1	1	3	5	6	3	3	4	3	4	5	5	7	7	8	12	8	14	E
15																1	1	3	7	7	7	5	5	7	7	3	1	0	5	7	6	4	6	7	8	4	3	4	4	8	15	E
16																	0	1	9	9	9	7	7	8	8	5	3	2	7	9	8	6	7	10	6	6	5	6	3	10	16	E
17																		1	9	9	9	7	7	9	9	5	3	2	7	9	8	7	7	11	7	7	5	7	2	9	17	E
18																			9	10	11	8	9	10	10	6	4	3	8	10	9	9	9	10	11	7	5	5	2	10	18	E
19																				0	0	0	1	0	0	4	6	7	2	2	3	2	2	4	5	7	6	6	13	7	19	E
20																					0	0	1	0	0	4	6	7	2	2	3	3	3	4	5	6	6	7	13	7	20	E
21																						0	1	0	0	4	6	7	2	2	3	2	3	4	5	6	6	7	13	7	21	E
22																							0	1	0	4	5	7	1	1	3	2	2	4	3	4	5	6	13	7	22	E
23																								1	0	2	4	5	0	1	2	1	0	3	2	3	4	3	11	6	23	B
24																									0	5	6	8	2	0	2	3	2	2	3	4	6	6	14	6	24	B
25																										3	5	7	1	0	1	1	1	2	2	3	6	5	12	6	25	E
26																											2	3	2	4	3	1	2	4	0	1	1	1	8	5	26	E
27																												0	5	5	5	5	4	6	3	2	1	2	4	6	27	E
28																													6	8	5	5	5	6	4	3	2	3	5	6	28	E
29																														1	1	0	0	3	1	2	4	5	11	5	29	E
30																															1	0	0	3	1	2	4	5	11	5	30	B
31																																0	0	9	0	0	2	1	10	3	31	B
32																																	0	1	0	1	3	3	10	4	32	B
33																																		2	1	2	2	3	10	5	33	E
34																																			1	0	2	0	10	1	34	B
35																																				1	2	2	9	3	35	B
36																																					1	0	8	2	36	B
37																																						0	7	2	37	E
38																																							1	7	38	B
39																																								4	39	E
40																																										
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40		

Figure 22 Table of Minutiae Extracted From Fingerprint Shown in Figure 21[37]

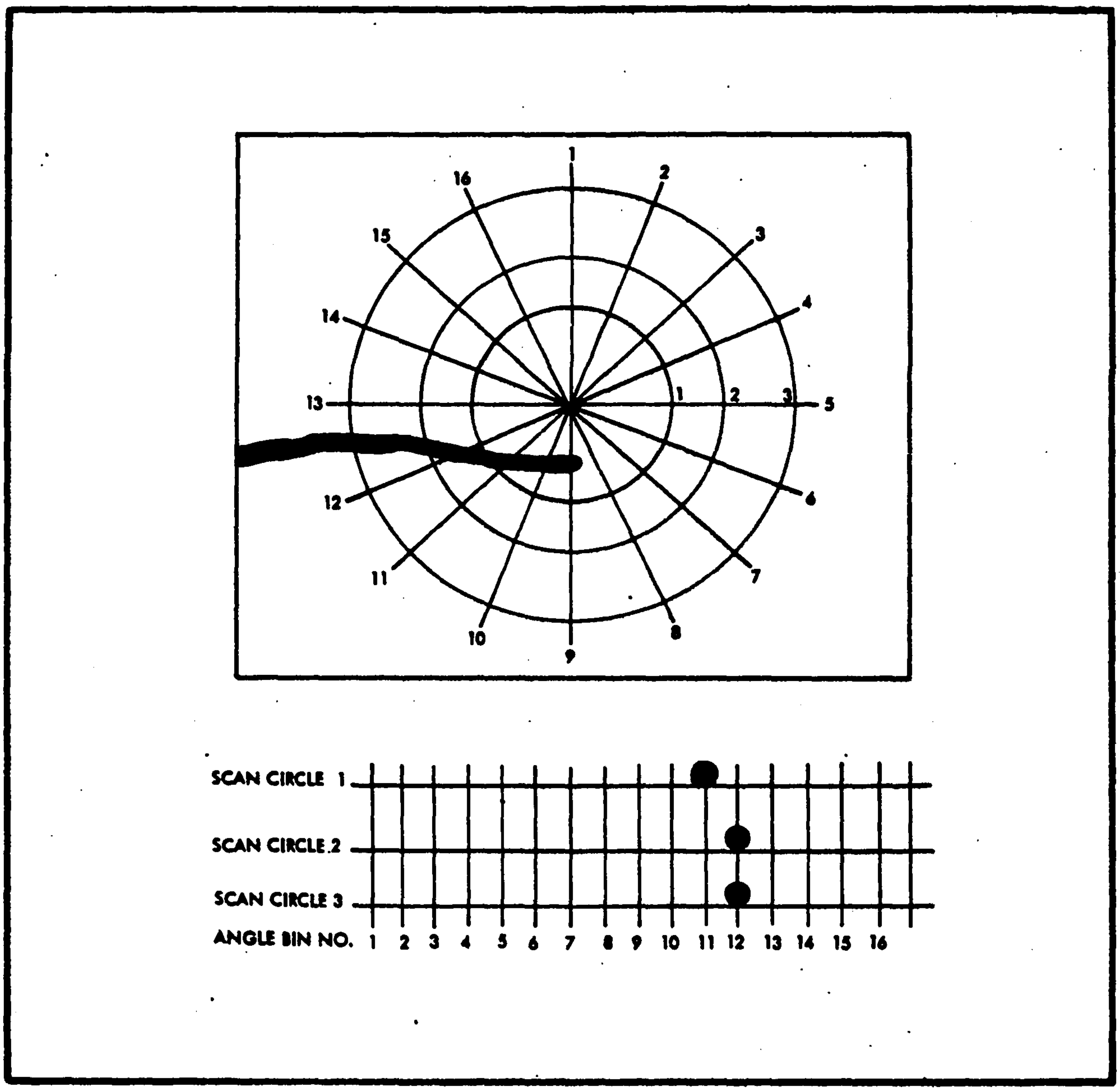


Figure 23 Scan Detecting Line End Minutiae[37]

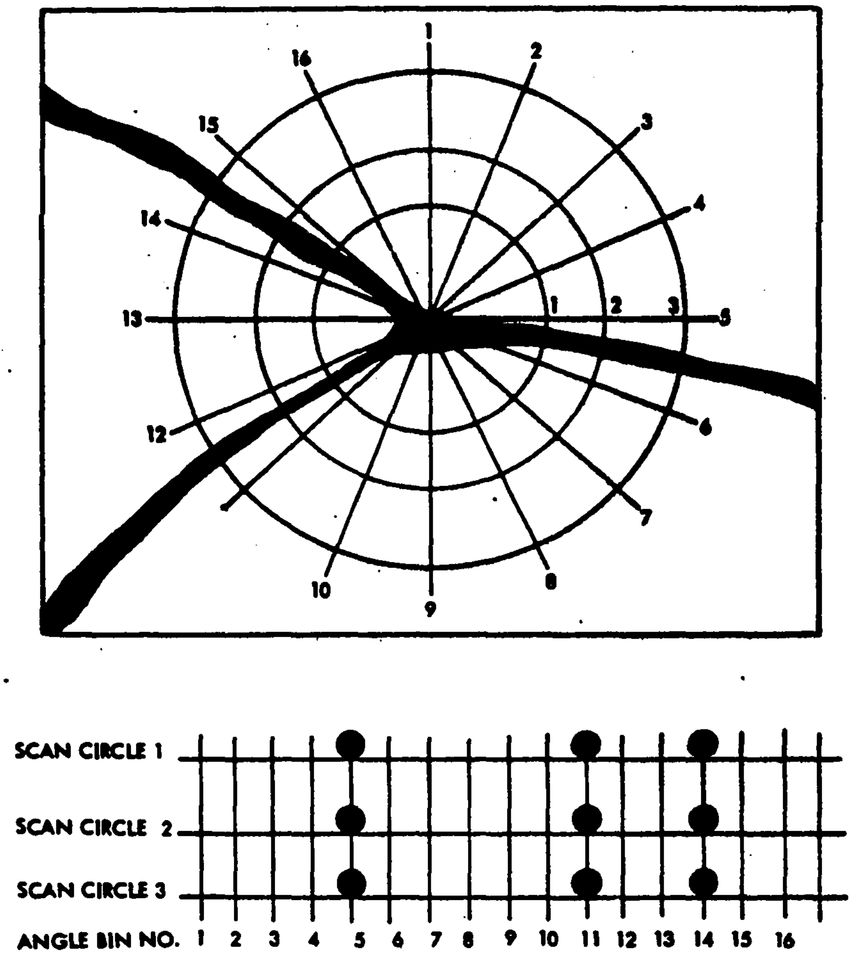


Figure 24 Scan Detecting Line Branch Minutiae[37]

continuous as assumed. The second is that ridges usually appear quite regularly one after the other. Many factors, including pore size in the enlargement of the print and narrowness of the scanning beam, indicate that some sort of filtering is needed in order to determine a ridge. Figures 23 and 24 seem to indicate no other ridges around the one of interest[37]. Figures 25 and 26 show the total classification when the other ridges are considered[37].

If it is assumed that no other ridges are in the search area, then the following argument should be considered.

The average distance between ridges, centre to centre, on the hand of an adult male is about 1 mm. Assume the area to be scanned is 30 mm by 20 mm. Then in order to assure that no two adjacent ridges are in the same scan area, the scan must be over a radius of 0.5 mm. (Ridges have a finite width.) The total number of scan patterns needed would be $600/(\pi/4) \cong 800$.

Assuming it takes on the average 3 seconds to totally scan, record, and interpret information from each scan pattern, it would take 40 minutes to identify each print. This is clearly nowhere near real-time identification - nor is it likely to be, unless some extremely fast equipment is developed.

This method is in general only a little better than the NYSIIS technique in that it eliminates the problems associated with ridge distortion due to uneven pressure during inking. This it does by using the number of ridges instead of the distance between them as a descriptor.

4.3.1.4 <u>General Comments</u>

Both of the methods in Category I used algorithmic approaches to the problem, and

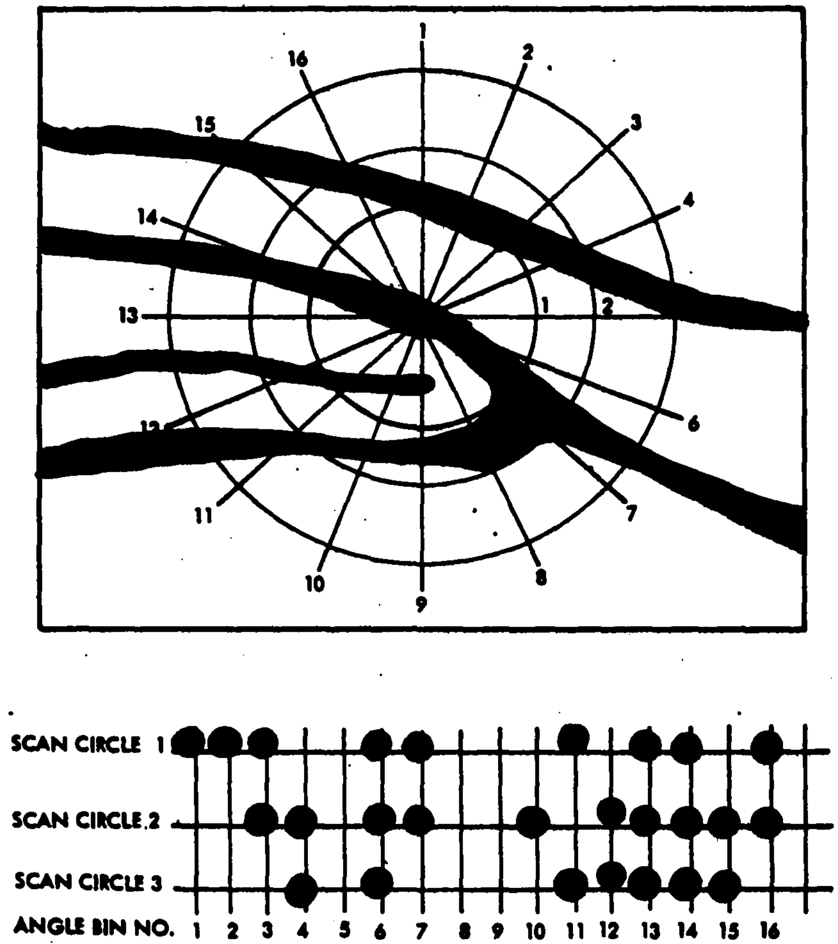
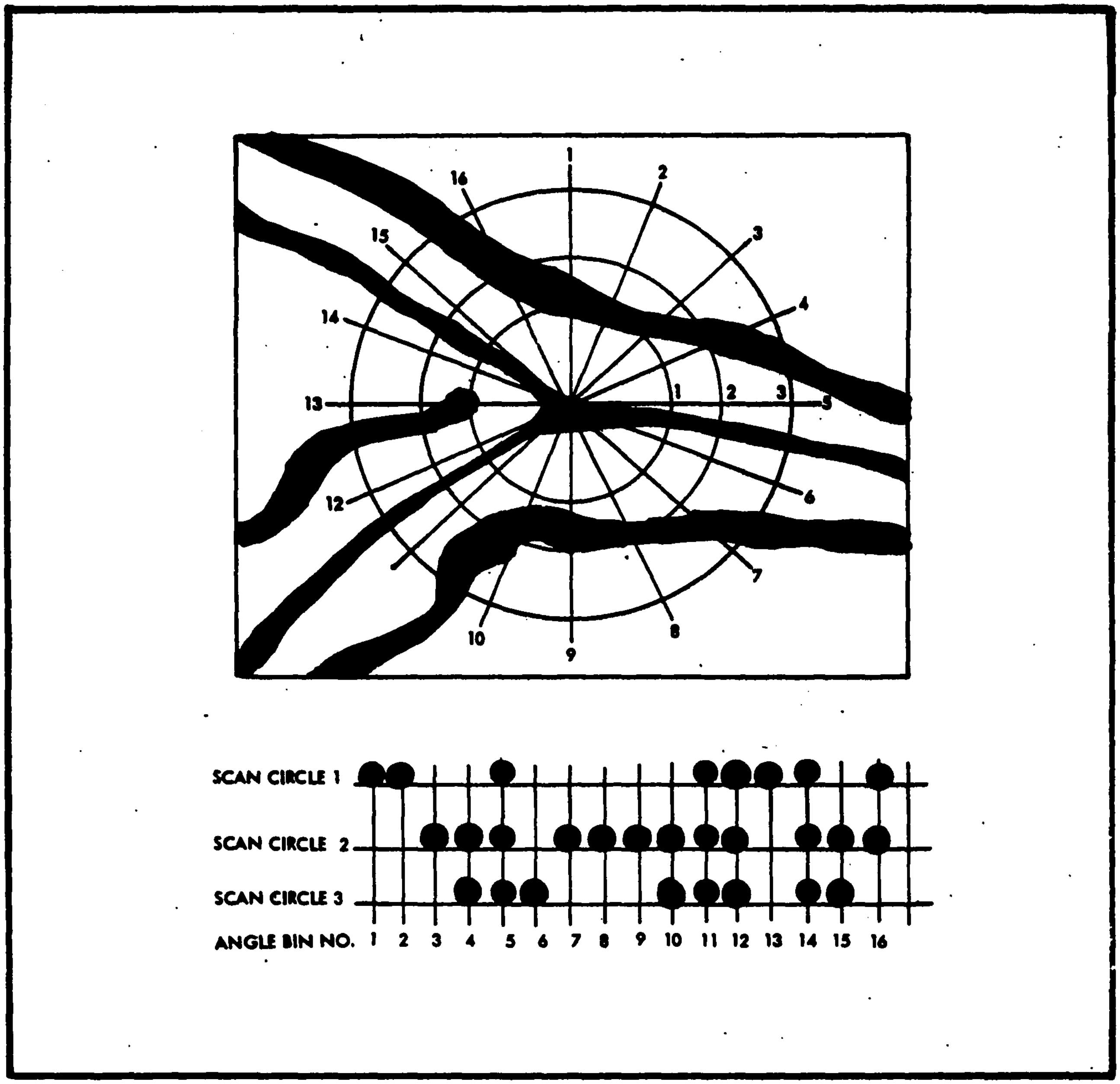


Figure 25 Revised Scan Detecting Line End Minutiae[37]



<u>Figure 26</u> Revised Scan Detecting Line Branch Minutiae[37]

actually suffer from both the 'Tourist' syndrome and the 'Forest-for-the-Trees' syndrome. Both rely heavily on the existence of minutiae classifiers and other pieces of equipment.

It is of interest to note that the Computer Corporation of America[38], in tackling general scene analysis problems, has generated some methods suitable for identifying fingerprint minutiae. Applied to a fingerprint, these methods have been highly successful in locating minutiae. One drawback is that noise due to poor print quality is sometimes identified as minutiae. This problem is being worked on, however, and when it is solved the CCA method will be totally suitable for minutiae identification.

Researchers in Category II (whole image) are perhaps more cognizant of the different interpretation media available. (See Section 4.3.2.) Most of their methods are divested of the 'Tourist' and the 'Forest-for-the-Trees' syndromes. The general tone of their research is perhaps best summed up by the following quotation:[28]

> "We feel that a classification based on the type of clues used in the Henry system cannot be accomplished by automatic means, within the present state of the electronic art."

With this thought, these researchers looked for other descriptors of the fingerprint, perhaps best termed 'gross descriptors'. They investigated heuristics and defined categories, categories not determined by the Henry system descriptors but just as effective if not more so in classifying and identifying fingerprints.

4.3.2 Category II

4.3.2.1 Photoelectric Fingerprint Analysis and Processing: Rabinow Electronics

In this treatment[28], examination of the problem begins with the scanning procedure.

The researchers realized from the start that the real fingerprint is of variable quality. The scan pattern[28] that was developed (Figure 27) has the following distinct advantages:

(1) It provides filtering so that the scanner sees the average line and is not greatly influenced by bits of dirt or breaks in the lines.

(2) The slot, rather than a spot aperture, provides a higher light level at the photodetector with improved signal-to-noise ratio.

The filtering provides a neighbourhood indication of relative black. It has also been found that different slot lengths and vibration amplitudes are appropriate for different parts of the print. The more rapidly varying the fingerprint, the shorter the slot should be.

The most important information extracted is that of the angle of the pattern with respect to a chosen reference axis. This angle-of-pattern information, together with a reference axis system, is used to characterize the fingerprint.

The reference system is determined by two operations. The first operation is to generate a point of 'core' by orthogonal trajectories. 'Core' here is not necessarily the 'core' of the Henry system. Figure 28 indicates the method[28] of orthogonal trajections. Starting as equally spaced lines at the top of the print and travelling through the print to cross each ridge orthogonally, the trajectories intersect at a point called the 'core'. To determine the reference axis, an expanding circular scan is carried out around the core until two 30° pattern lines are found as indicated[28] in Figure 29.

The classification method is called the Octant-Slope system. Here the reference circle is divided into eight area octants, with the reference line placed on the junction between octants 1 and 8. Next, the average slope of the ridges in each octant is determined. Finally, the print is classified by the octant-slope relationship. The whole

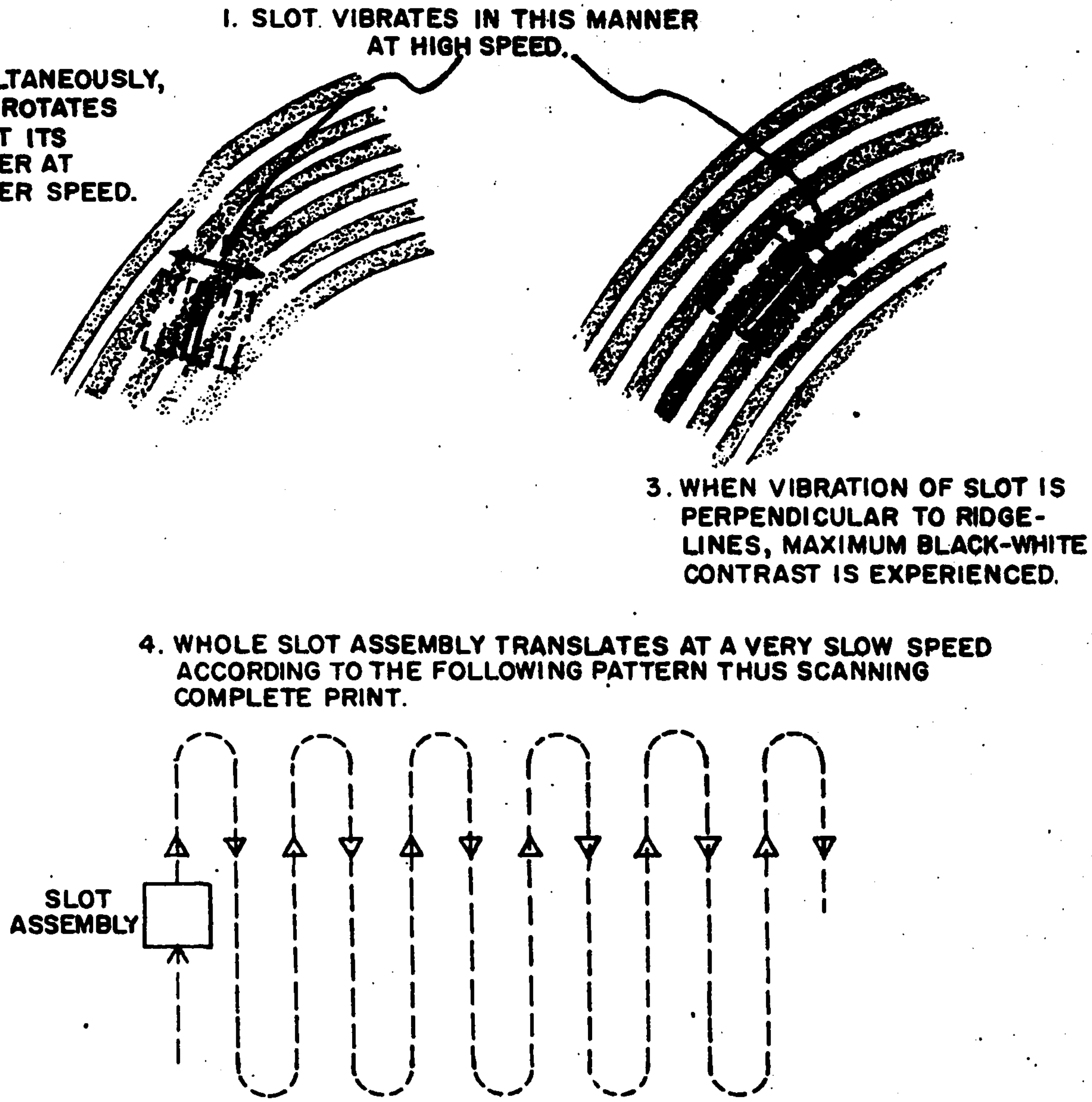


Figure 27 Diagrams of the Motions Used in Slot-Scanning of Fingerprints[28]

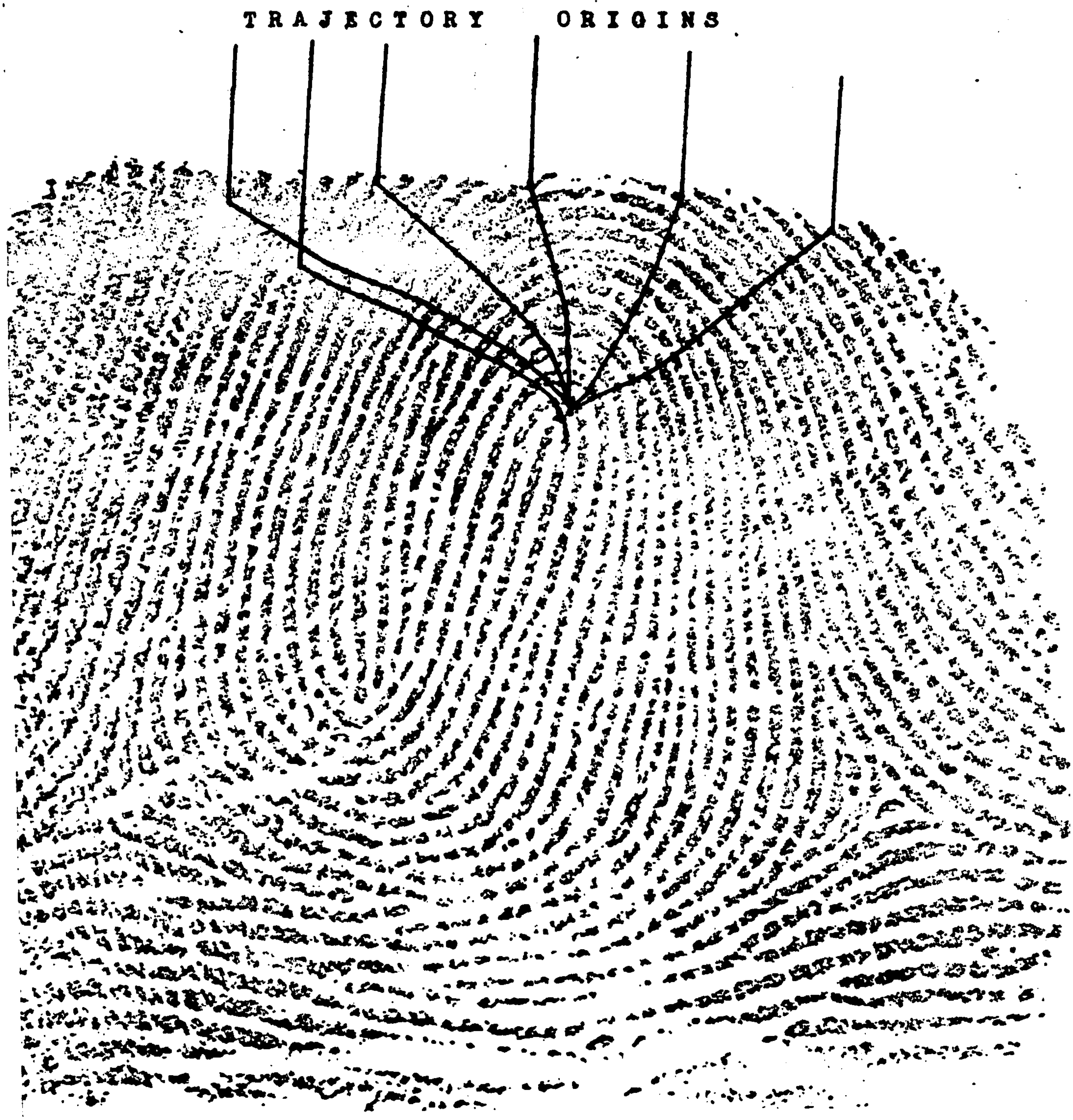


Figure 28 Tracing Orthogonal Trajectories[28]

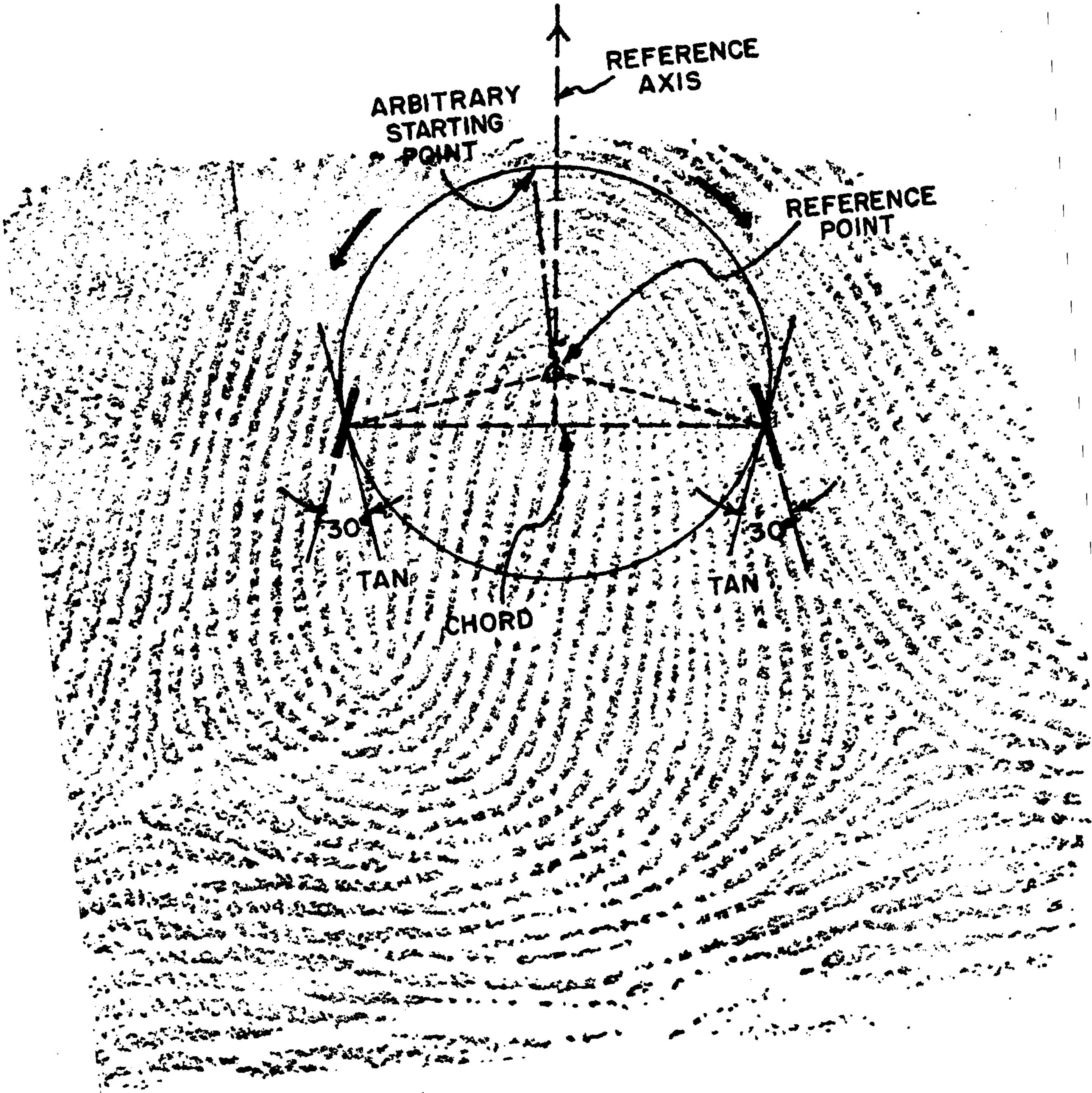


Figure 29 Determination of Reference Axis[28]

reference and classification scheme is illustrated[28] in Figure 30.

The interesting points are that the reproducibility is very good and the resolution into distinct classes is extremely high. To quote:

> Using this method, the theoretical number of classes for a single print would be somewhat over two hundred eighty trillion. However since the ridge lines are generally continuous, the slopes in adjacent areas are related. Also those at the top of the print are roughly circular. For these reasons, better than 90% of all prints would be contained in about 200 classifications.
>
> The maximum number of classes using all ten fingers of an individual would be 10^{200}. This figure is based on the estimate of 200 probable classifications for each finger. Because there is some relationship between the fingerprints of a given individual, the probable number of classes would be less. We do not have sufficient data at present to estimate this figure[28].

This system is derived from essentially heuristic considerations that try to answer questions such as: Do we need a reference system? If we need a reference system, can we devise one that is better than those now existing? Can we effectively and efficiently classify fingerprints using this reference system?

One problem with the system is that the fingerprint has to be presented to the scanner in a certain rotational configuration. Figure 31 indicates the possible points of core determined if other rotational configurations are used.

All in all, this method presents an attack on the problem that can best be described as the beginning of the application of pattern recognition techniques.

The second method presented in this section is essentially a prospectus and illustrates a highly heuristic technique.

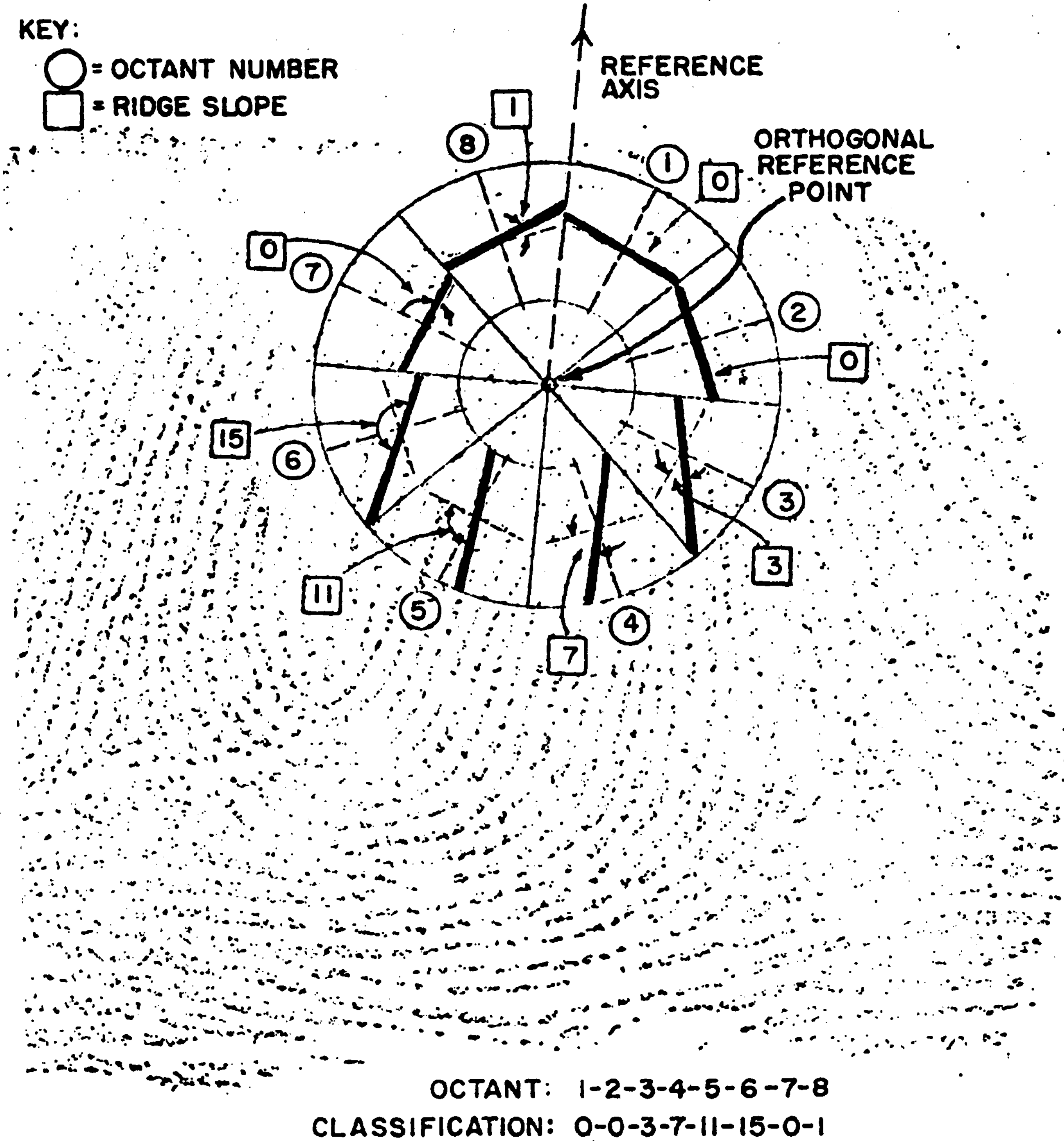


Figure 30 Use of Orthogonal Reference Point and Reference Axis to Establish Octant Grid and Measure Average Slopes[28]

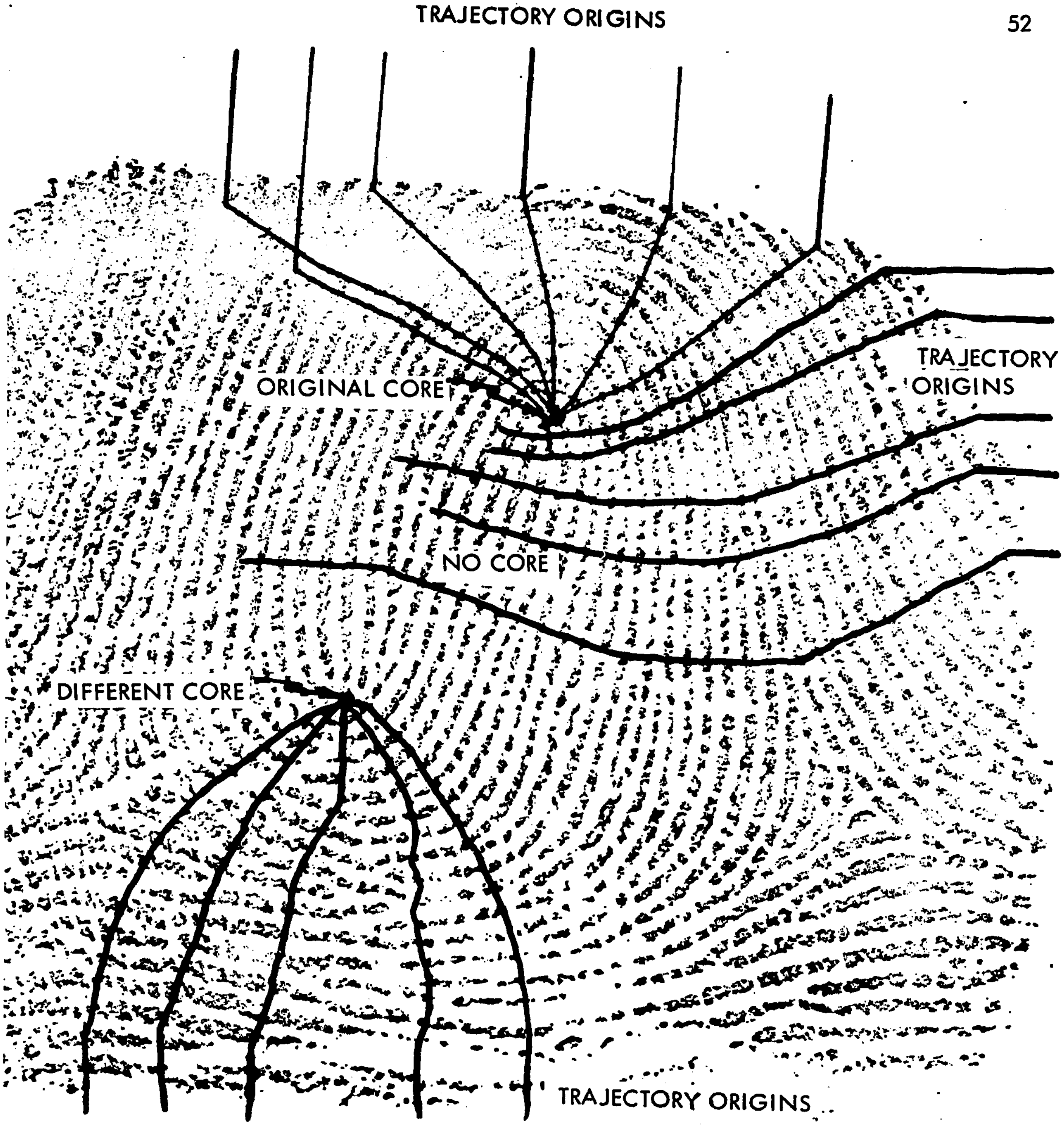


Figure 31 Other Orthogonal Trajectories Traced

4.3.2.2 Automation of Fingerprint Identification: Anthony Paolantonio

Mr. Paolantonio[24] suggests that the fingerprint be scanned in nine different patterns and the number of ridges crossed in each scan be tallied. His basic argument is:

> Because no two fingerprints are alike, the number of lines scanned in each print would be different, hence a quasi-random number would represent the fingerprint when scanned in this manner. In addition, if the print were to be scanned in more than one pattern shape, it is obvious that a series of quasi-random numbers would be recorded[24].

A counter argument is that although no two fingerprints are alike in detail, many fingerprints are the same in terms of gross descriptors such as whorl or loop. Mr. Paolantonio is apparently trying to define a high resolution of a gross descriptor. This in itself is not a bad idea but the size of the fingertip as well as the size of the ridges, varies from individual to individual, and the narrow ridges are associated with the smaller fingertips. Thus, the total number of ridges intersected by a straight line varies little, either between individuals or between prints of an individual. The number of intersections, though, depends on how the print was made, and thus on how much of the print is present. Basically, there are enough ridges to fill a fingertip, and a fingertip is finite in size.

There may therefore be no justification for assuming that different scan patterns will generate enough different quasirandom numbers to provide a high enough degree of classification resolution. Further, finding an invariant place to start the scan patterns is a nontrivial problem not apparently approached by Paolantonio.

This method requires further study for fair evaluation. (See Chapter V.)

The final method to be discussed is a heuristically directed topological algorithm. The devisors of this method observed the invariance of the Henry system under rotation, translation, or even degeneration of the print and were led to investigate some type of topological coding. Their heuristic interpretation and use of the accumulated data gives this method advantages over the Henry system.

4.3.2.3 Automatic Fingerprint Interpretation and Classification Via Contextual Analysis and Topological Coding

Figures 32 and 33 indicate the basic system and processing concepts of the automatic fingerprint-processing system[12]. The input system performs three functions: spatial quantization, amplitude quantization, and elementary noncontextual spatial filtering.

The spatial quantization determines how much detail can be observed. The amplitude quantization generates a black-white digitized code such as the eight-level gray code previously mentioned. Noncontextual filtering essentially generates a machine sense of relative blackness.

The purpose of the input system is to form an idealized print (Figure 34) for the interpretation system[12]. In generating the idealized prints, however, such things as contiguous or partial ridges are not seen. The interpretation system first generates the classifying print by contextually filtering the idealized print, and then classifies the print.

Contextual filtering consists of heuristically determining whether or not a ridge discontinuity is a gap or an ending, and whether or not a ridge fill is spuriously contiguous or actually a detail of the print. Here gaps and contiguities are considered noise. Figure 35 illustrates contextual filtering[12].

Next, top nodes are scanned downward until a point of 'core' is reached. A top node is defined as a point about which the ridge has a locally maximum curvature. A typical scan is illustrated[12] in Figure 36.

Finally, each ridge is traced and encoded topologically (Figure 37)[12] starting

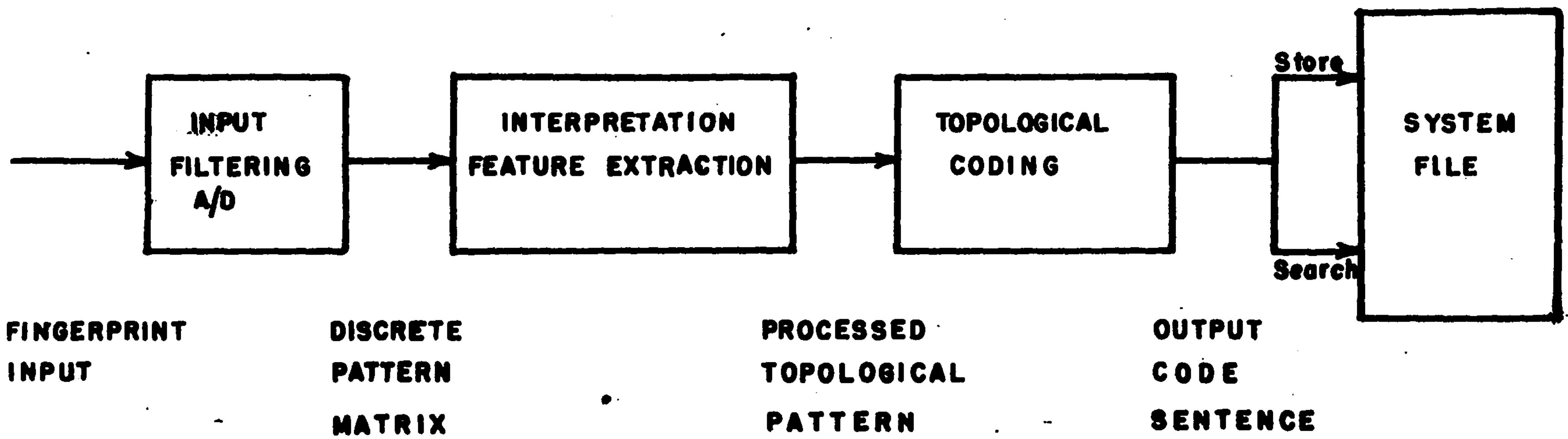


Figure 32. Automatic Fingerprint Processing System[12]

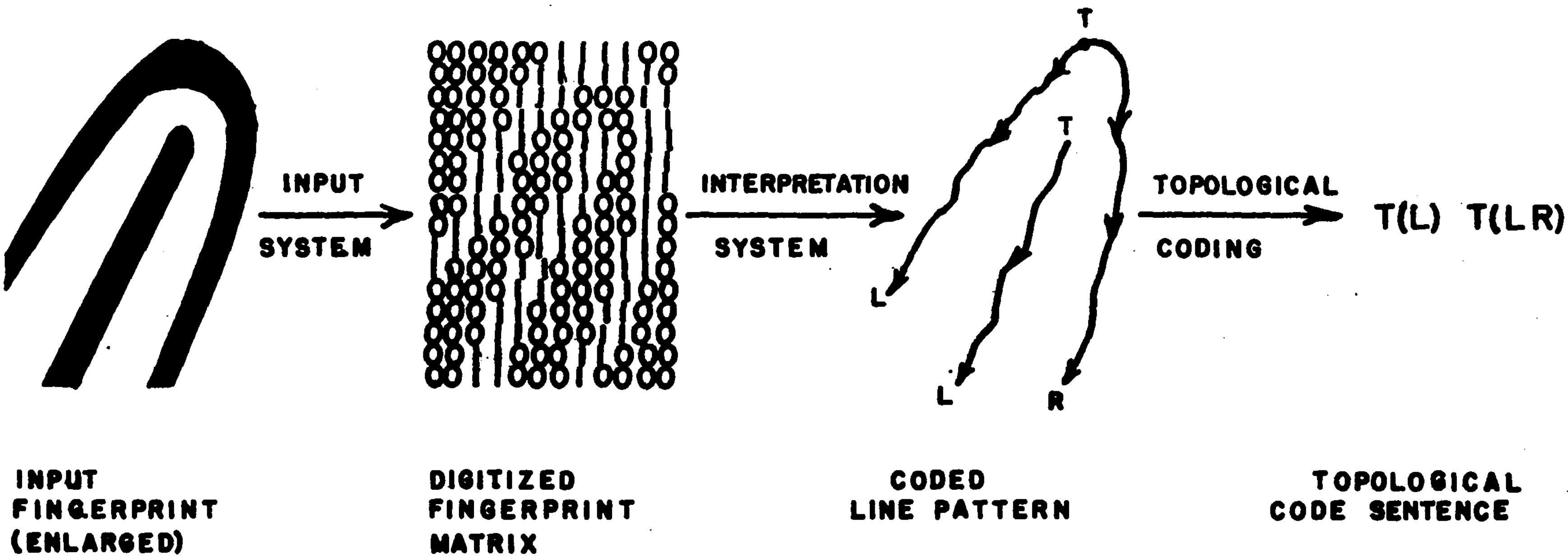


Figure 33. Fingerprint Processing[12]

Figure 34. Sample Idealized Print With Ridge Gaps [12]

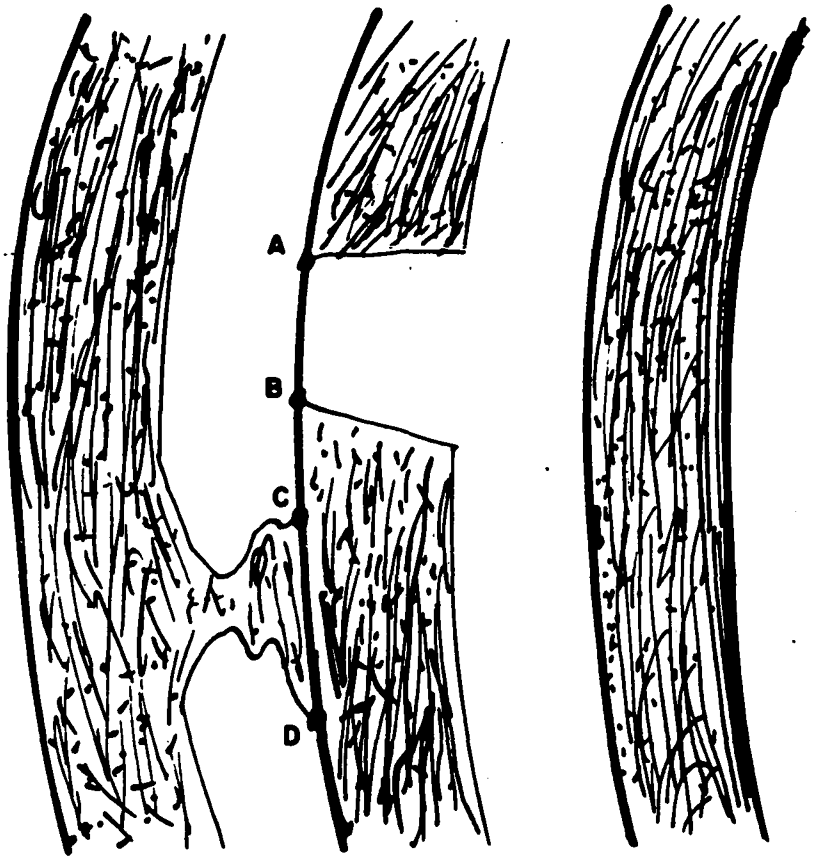


Figure 35. Contextual Filtering of Ridge Gap and Contiguous Ridge[12]

KEY: A-B = Filtered Ridge Gap
C-D = Filtered Contiguous Ridge

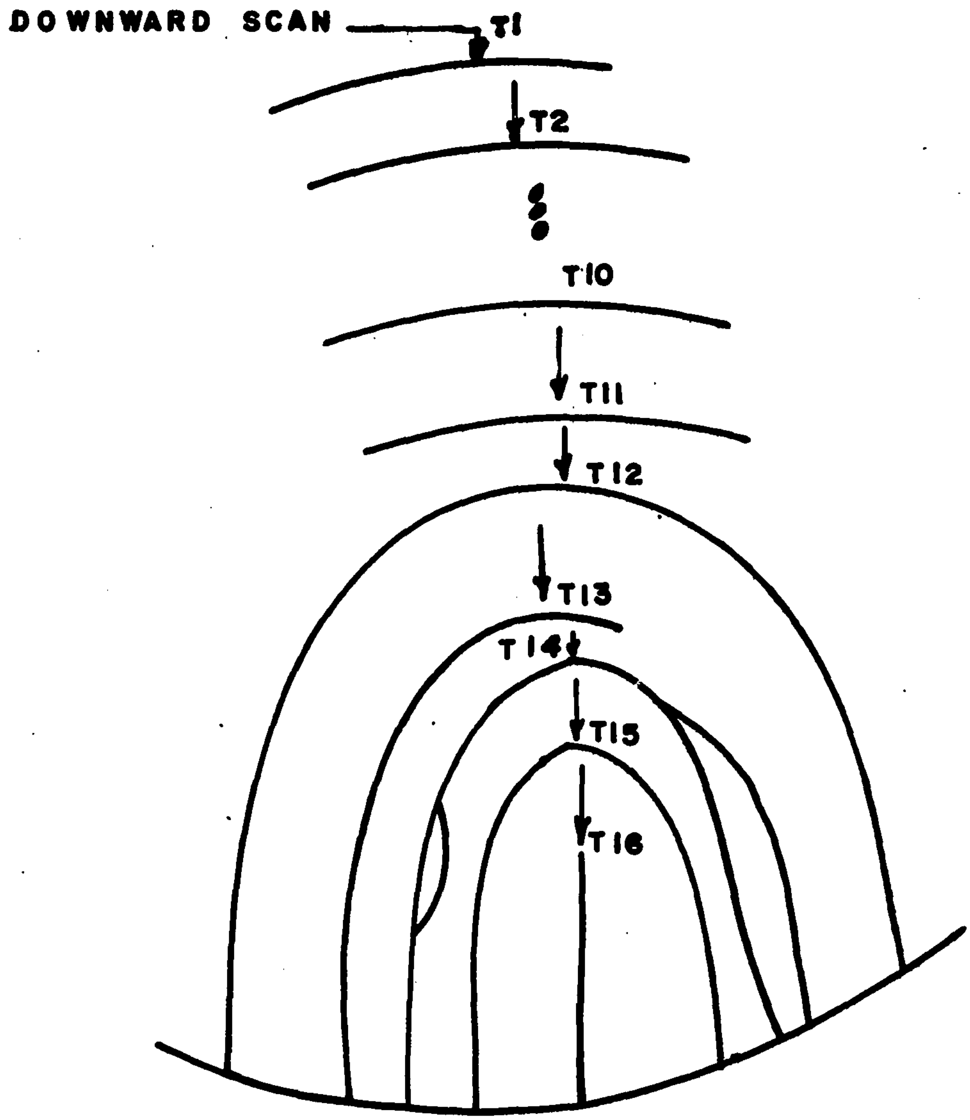
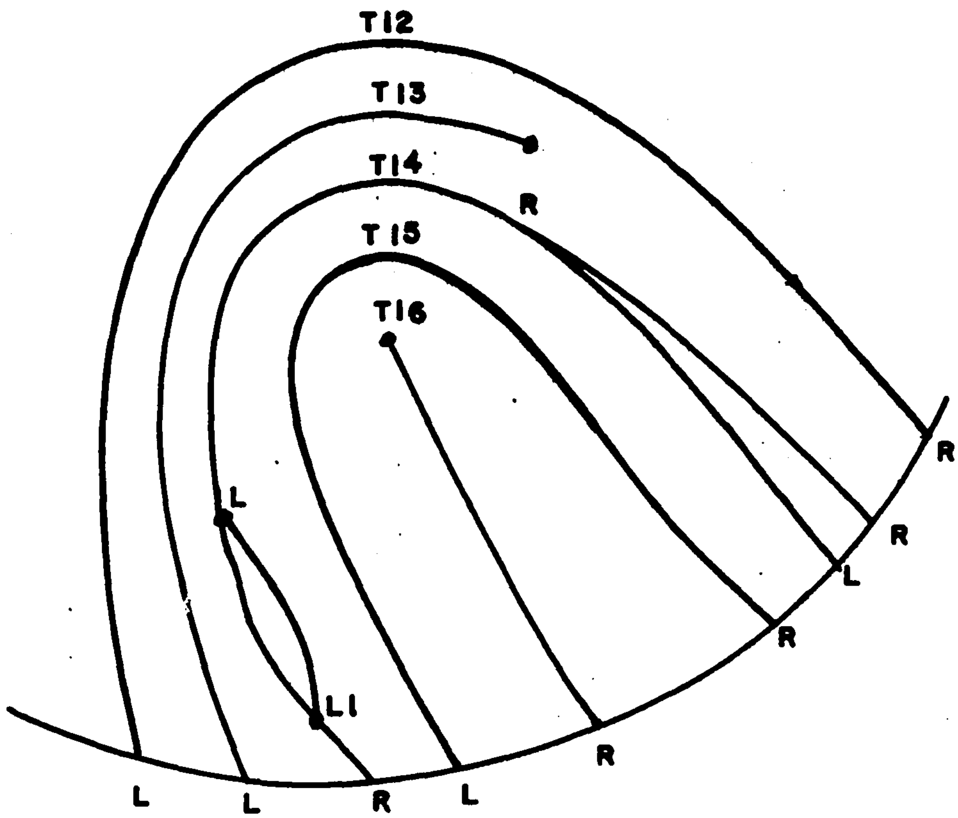


Figure 36. Input Processing Operation for Sample Print[12]



TOPOLOGICAL CODE SENTENCE:

T(R) T(LR) T(L(L1(R)L1)R (LR)) T(LR(O)) T(LR)

Figure 37. Topological Coding for Sample Print[12]

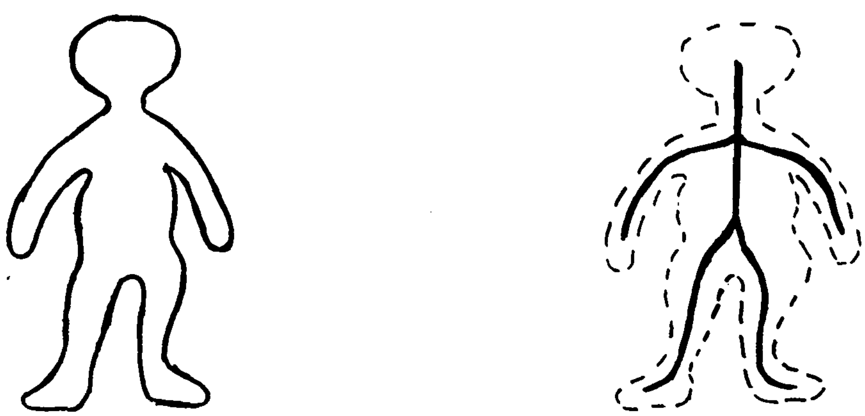
from the innermost top node and working outward.

One problem noted with this method is that certain types of ridge gaps might be filtered out, thus reducing the amount of classification data. Another problem is that a different rotation of the fingerprint will define a different top node and possibly a different code sentence. This is so, because the concept of a top node is that of a local rather than a global point of maximum curvature of a ridge. Nevertheless, this is the most promising of any methods so far presented for automatically classifying fingerprints.

4.3.2.4 Other Methods

This section briefly outlines other Category II attacks on the problem.

In his work on shape descriptors, Blum[1] looks at the boundary of a shape as a wavefront, reasoning that if the wavefront is allowed to propagate in time, the intersection of the Huyghens wavefronts will generate a medial axis descriptor of the shape. One of his examples of a medial axis descriptor is the stick figure of a man, as seen in Figure 38.



(a) Closed contour figure of a man

(b) Medial axis descriptor of Figure 38a

Figure 38 Blum's Shape Descriptor

The same technique applied to a fingerprint pattern may produce a unique general descriptor that can be coded by methods described by Freeman[8,9,10] (see Figure 39). To

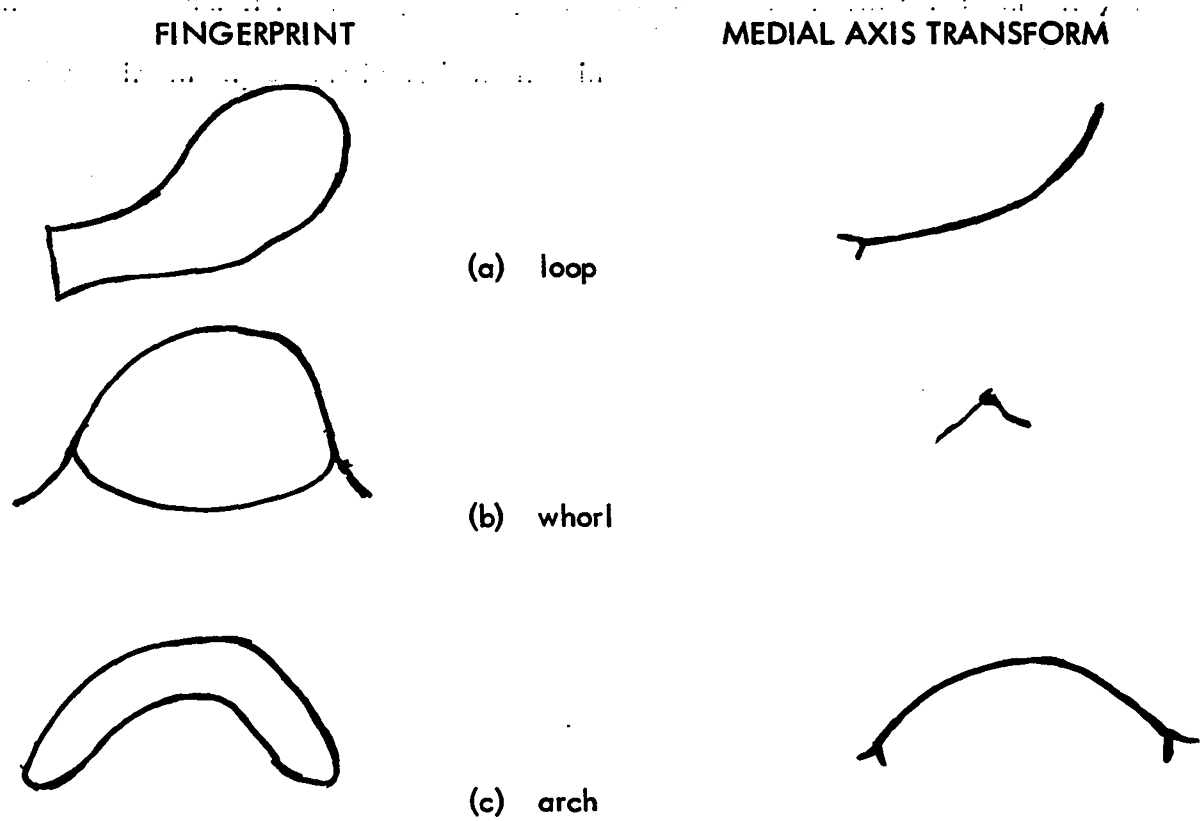
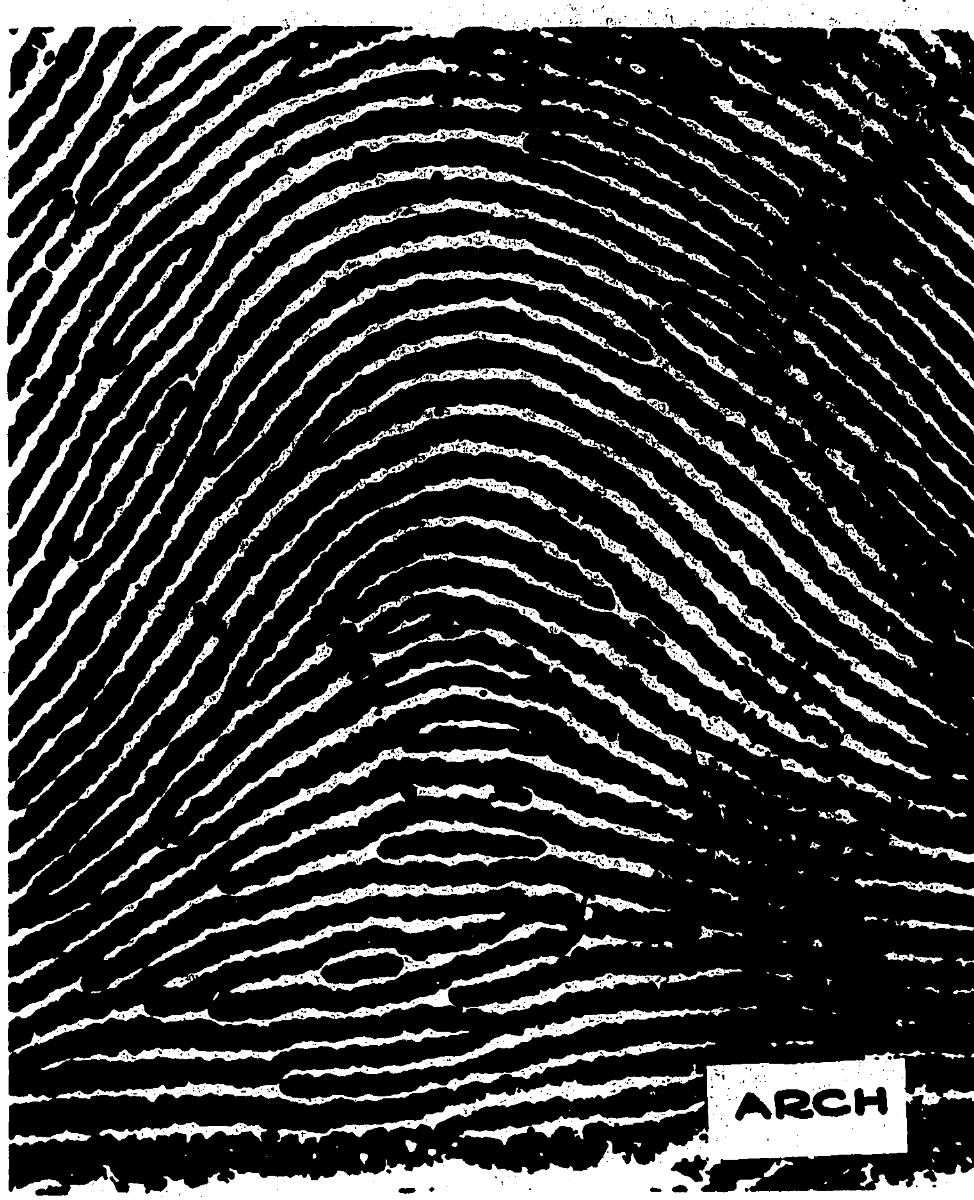


Figure 39 Blum's Method Applied to Fingerprints

generate these simplified loops, whorls, and arches from real prints mechanically, however, would require highly sophisticated engineering. How is the machine to determine an average line representation of the print?

Investigation into the 'average line' generated by the Rabinow Electronics scanning method indicates that representative sets of lines can be formed. A fingerprint (Figure 40) can be reduced to an average fingerprint (Figure 41) and then be dealt with by using medial axis descriptors. The medial axis can then be coded for curvature or intersection or other properties in order to sort the prints by these properties.



<u>Figure 40</u> Fingerprint[32]

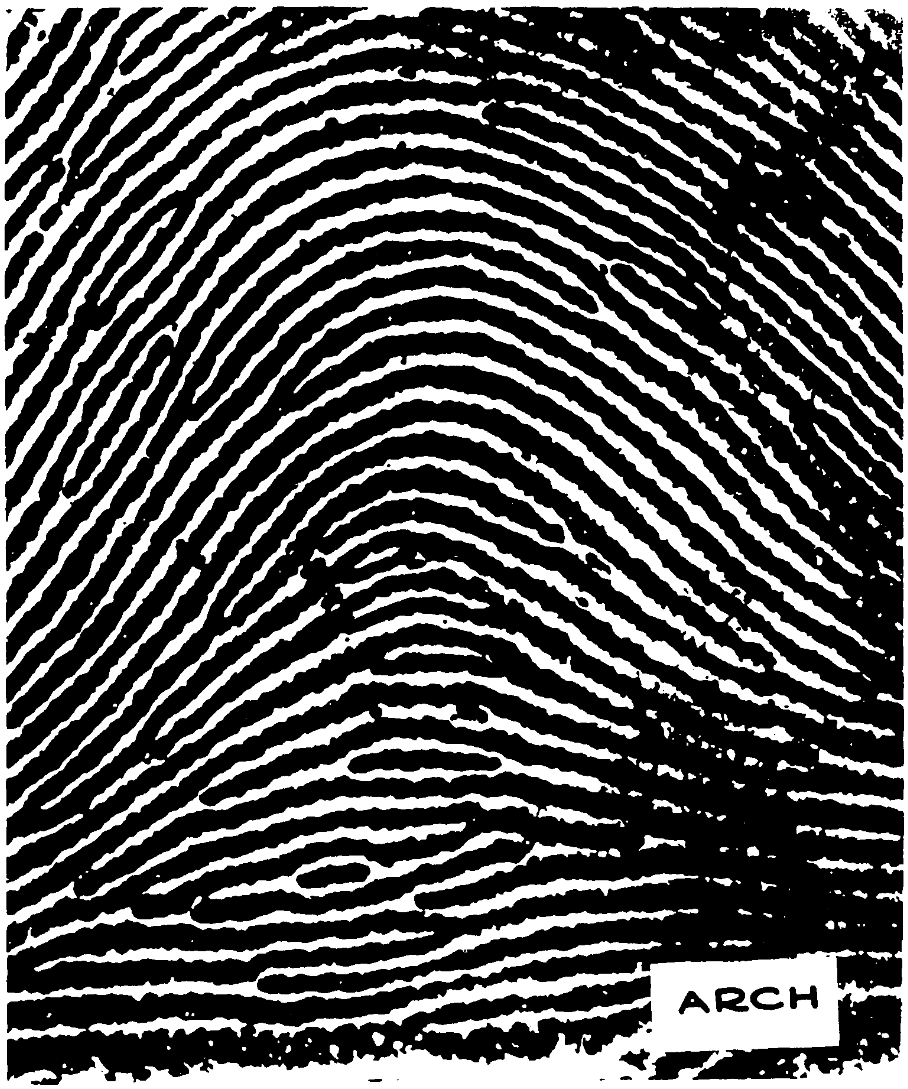


Figure 40 Fingerprint[32]

Figure 41 Average Fingerprint Extracted from Fingerprint in Figure 40 (Heavy Lines)

Figure 41 Average Fingerprint Extracted from Fingerprint in Figure 40 (Heavy Lines)

In another method, similar to the above but an adaptation of a method of class separation proposed by Rosenfeld and Pfaltz[31], the object being analyzed is fenced in by a region of area (Figure 42). Next, smaller regions are marked in the area, and the

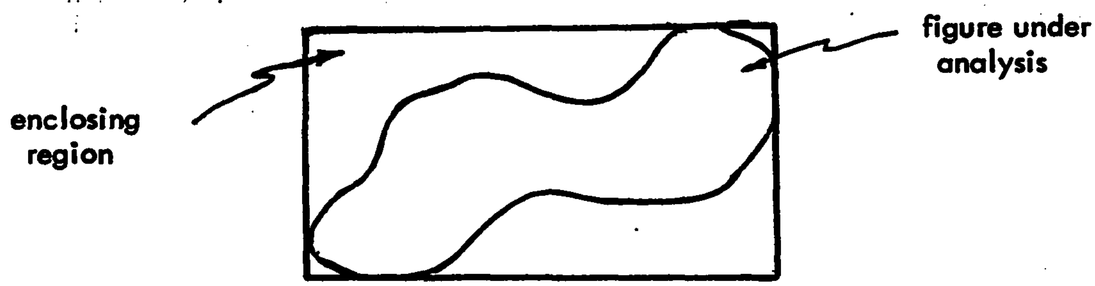


Figure 42: The Rosenfeld and Pfaltz Method Applied to an Arbitrary Figure

number of these regions that touch the contour of the specimen are tallied (Figure 43).

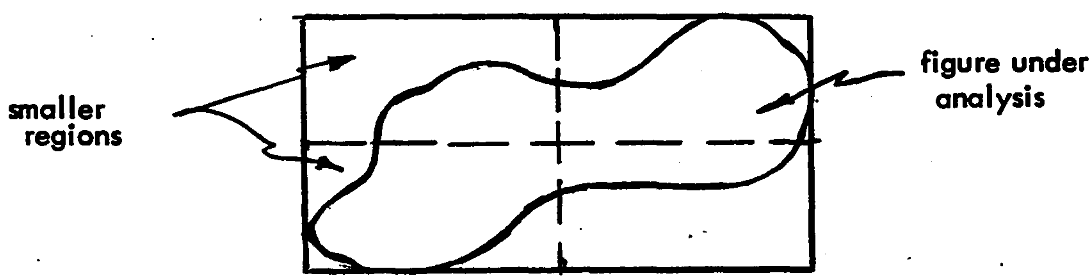


Figure 43 Inlaying of Smaller Regions

This inlaying of regions continues until a previously determined size of region threshold is reached. The information obtained along the way is plotted as a graph (Figure 44). It is hoped that different types of fingerprints will generate line graphs that can easily be discriminated from one another, thus effectively classifying the fingerprint.

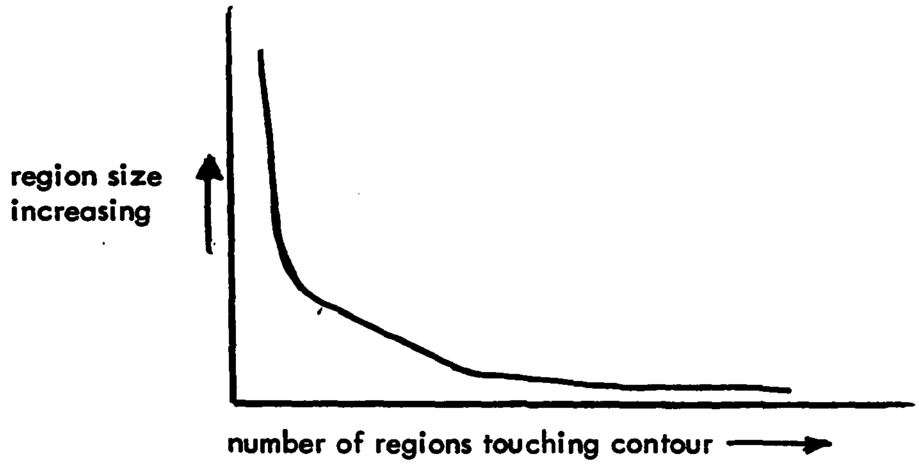


Figure 44 : Data Obtained from Rosenfeld and Pfaltz Method

The major objection to these last two methods is that they deal with gross descriptors of an object, and there is not enough classification resolution to distinguish one fingerprint amongst others of a generally similar type. The first of the two methods may be looked upon as an initial separating, not a classifying, process. The resolution of classification is extremely low, so it is used only to split fingerprints into such groups as may be analyzed by different algorithms or heuristics. The full classification scheme will have an inherent partitioning or hierarchy that will direct different fingerprints to different algorithms, and the particular algorithm will then classify the fingerprint.

The lack of resolution is noticed more acutely in the second of the two methods. In tests of this algorithm on four fingerprints, easily recognized as four different fingerprints by even an inexperienced observer, the method indicated these four prints to be essentially the same. The differences between the line graphs are so small as to be attributed to noise and not actual differences in the fingerprints.

4.4 Conclusions

Of existing methods, Hankley's is perhaps the best for the following reasons:

(1) It provides a high degree of resolution, generating over 10^{14} classes while using only a few ridges near the 'core'.

(2) The interpretation time for each print is under 2 seconds.

None of the other methods combine both of these attributes. Noting, however, that most of the input subsystem indicated (Figures 32 and 33) was actually manually effected, and that certain pertinent ridge characteristics might be filtered out by Hankley's contextual filtering, it is the author's opinion that there is still a lot of work to be done before fingerprint analysis can be fully automated. Further progress might be made by rearranging Hankley's method, generating a new classification scheme entirely, or developing man-machine systems.

In summary, automatic fingerprint analysis was presented in the context of a pattern recognition problem. Existing solutions, as well as the problems associated with these solutions were explained. Finally, other methods were put forth as possible areas of research in trying to fully solve the problems associated with automatic fingerprint analysis.

The following chapters present the author's investigations into the problem of automating fingerprint analyses.

CHAPTER V

EXAMINATION OF THREE TECHNIQUES

5.1 Introduction

In this chapter, the author examines three methods in a non-machine context, and the results obtained from these analyses are presented. The three methods tested are:

(1) The method of Paolantonio,

(2) The method of Blum, and

(3) The method of Rabinow Electronics.

The reason for choosing these three is that they are perhaps the most representative of the various techniques presented in the literature.

The method of Paolantonio, which has not heretofore been examined in the literature, represents those treatments which purport to totally classify fingerprints by using analyses which typically involve some type of random search. This type of analysis disregards both the gross shape characteristics of the fingerprint and the minutiae or ridge characteristics. Paolantonio originally suggested his technique as a prospectus, and to the author's knowledge, no actual tests of the technique have, to this writing, been made on fingerprints.

The method of Blum is typical of those techniques, including the manual Henry system, which attempt to use the overall or gross characteristics of a fingerprint as the unique classifying agent. It must be noted that the method of Blum was developed by this author using Blum's techniques of shape extraction, and that this approach has not been previously considered in the literature. To this writing, none of Blum's techniques have been applied to fingerprints.

The method of Rabinow Electronics represents those approaches that seek to classify fingerprints by selectively considering specific pieces of information in a fingerprint. This method does not solely consider the 'gestalt' or gross characteristics (as does the method of Blum), but it does reject information about the ridge minutiae (as does the method of Paolantonio). However, other information such as the average ridge slope in a small region is used in lieu of the minutiae.

5.2 The Method of Paolantonio

Paolantonio proposes the use of an optical scanning technique for the analysis of fingerprints[24]. The method consists of scanning a given fingerprint usine nine different scan patterns, and tallying the number of times a given scan pattern intersects the ridges of the fingerprint. Paolantonio suggests that the resulting tallies should be nine 'quasi-random' numbers and that these numbers fully identify the fingerprint.

The author carried out an experiment using one scan pattern on fingerprints B-2, B-5, B-6, B-7, B-8, and B-9 of Appendix B. The scan pattern used was a series of vertical parallel lines originating from the top of each fingerprint. In all cases, the physical size of the fingerprints was very nearly equal. The number of intersections found and tallied for each line of the scan pattern in each fingerprint is presented in histogram form in Figures 45 through 50. Also, the total number of intersections found in each fingerprint for the full scan pattern is displayed in the respective histogram.

One should note the two types of error regions defined in the histograms. The first type is indicated by the line shading and the second type is indicated by the stippled shading. The line shading represents that error which arises in trying to repeat an analysis of a fingerprint with the same scan pattern. This is an alignment error, and is

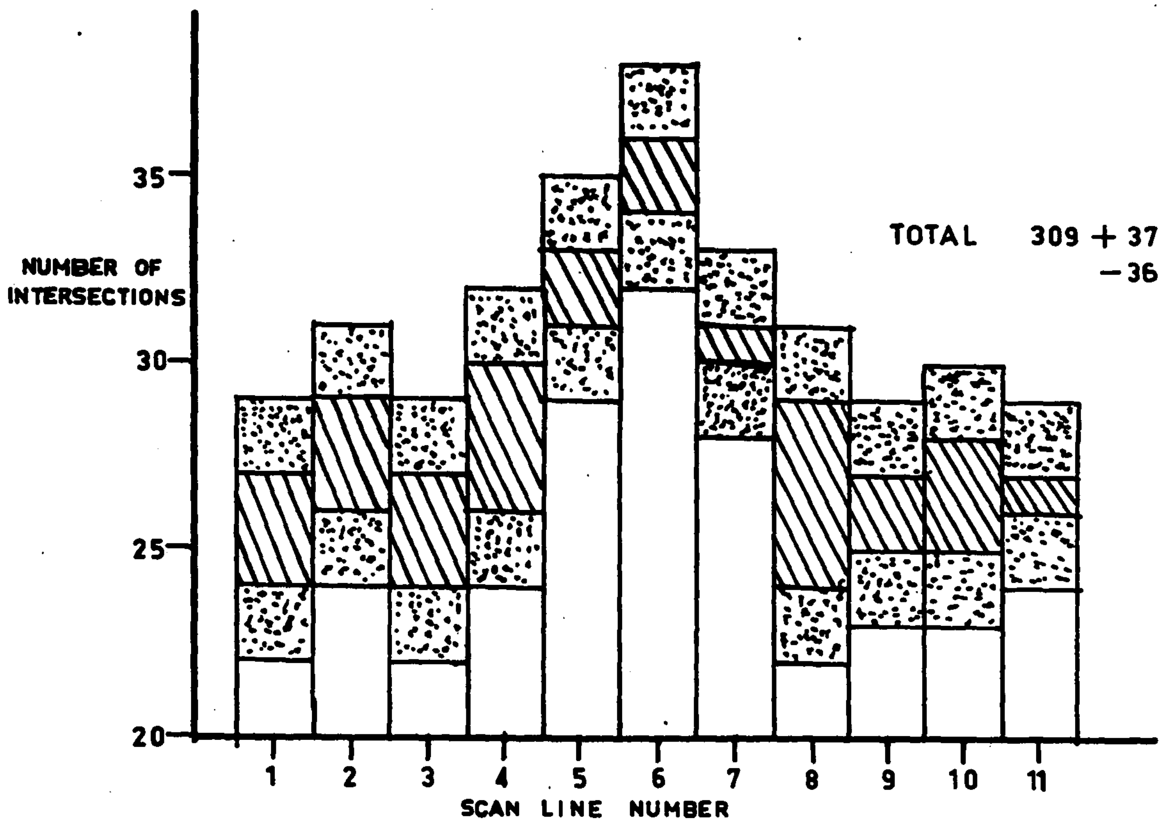


Figure 45. Histogram – Twinned Loop

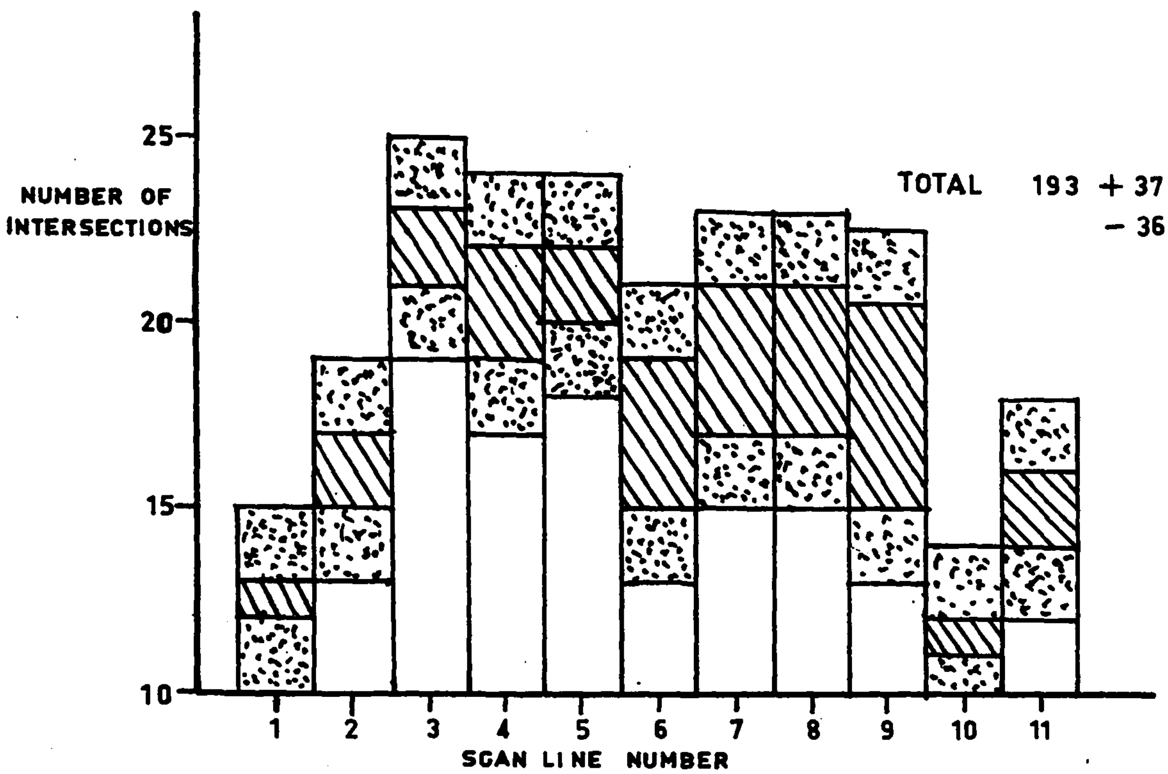


Figure 46. Histogram – Tented Arch

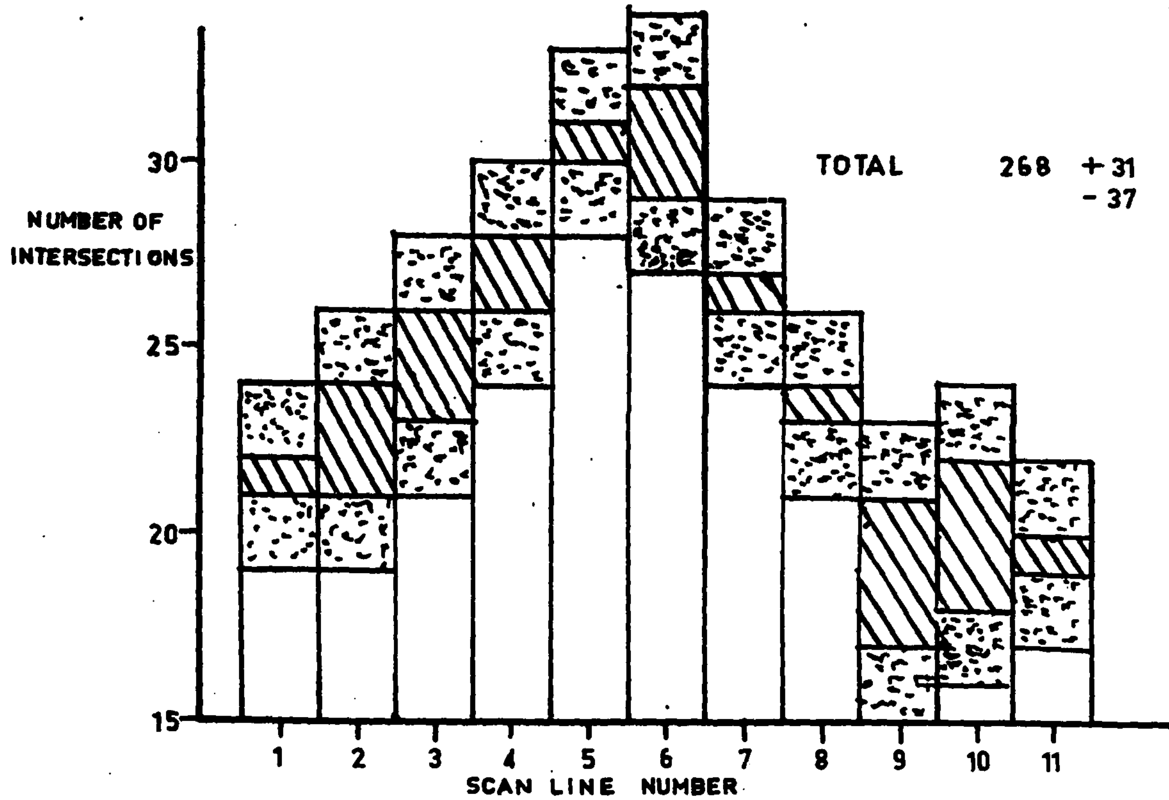


Figure 47. Histogram — Arch

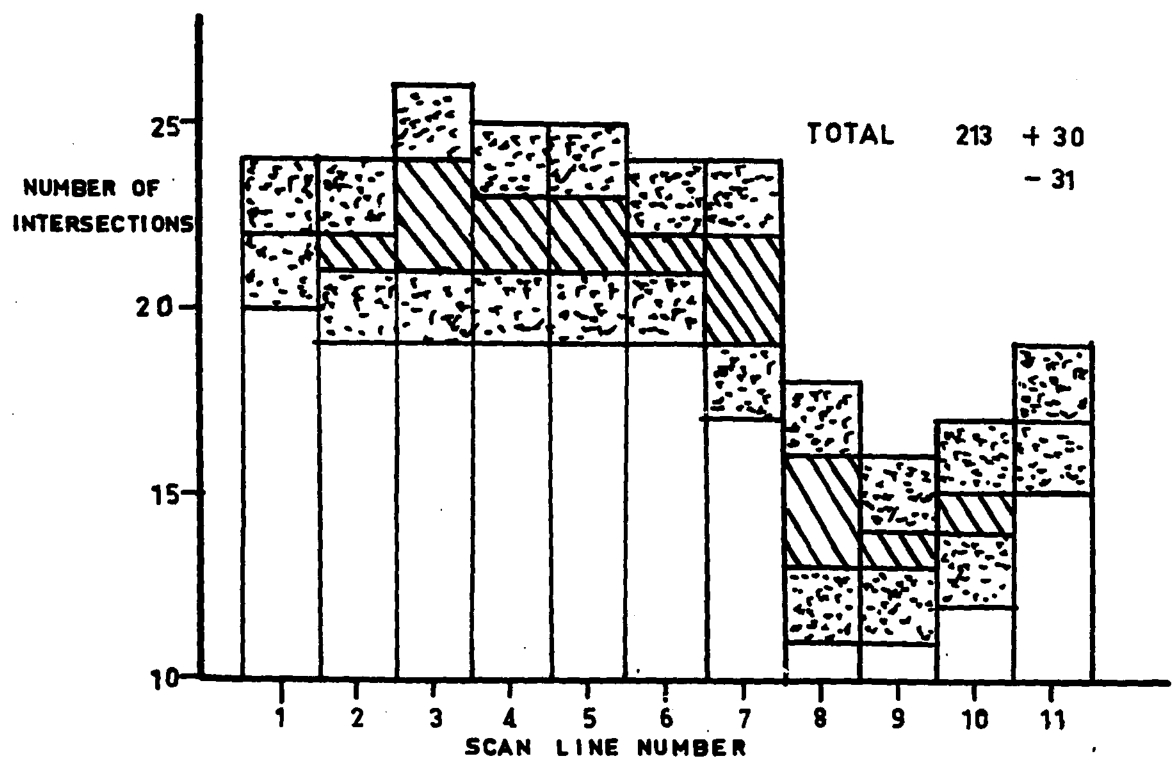


Figure 48. Histogram — Radial Loop

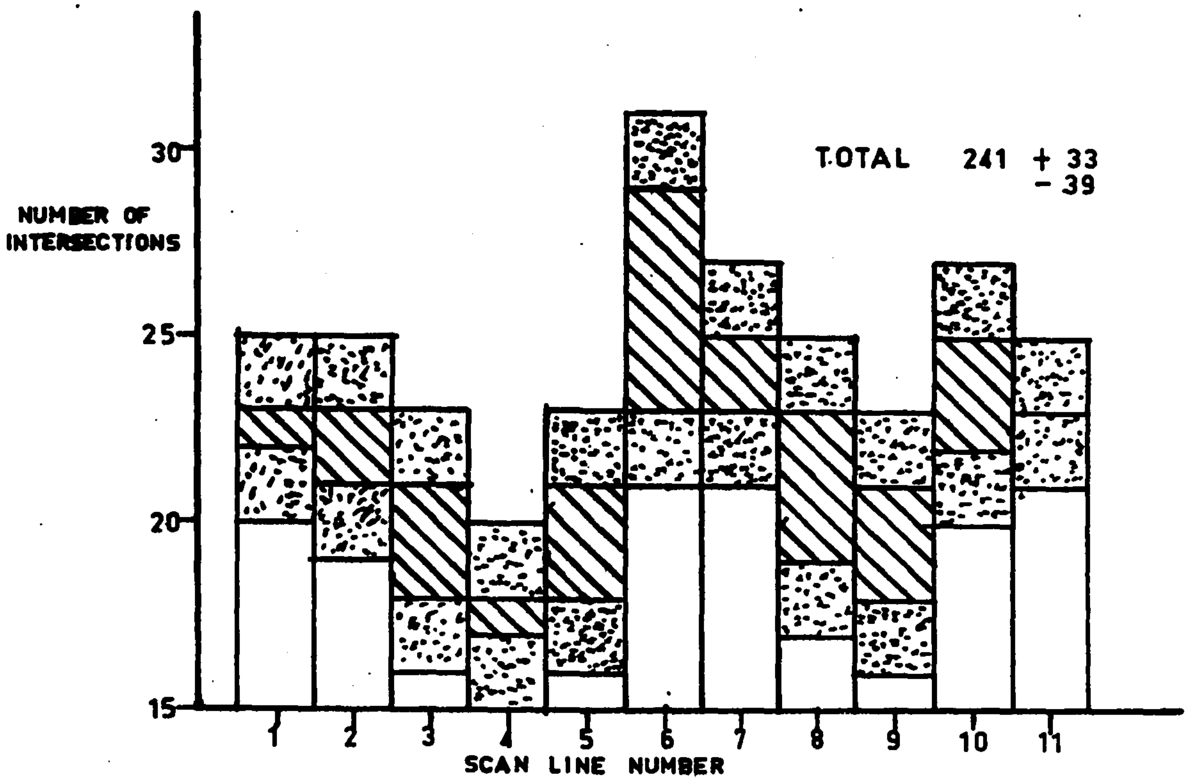


Figure 49, Histogram- Ulnar Loop

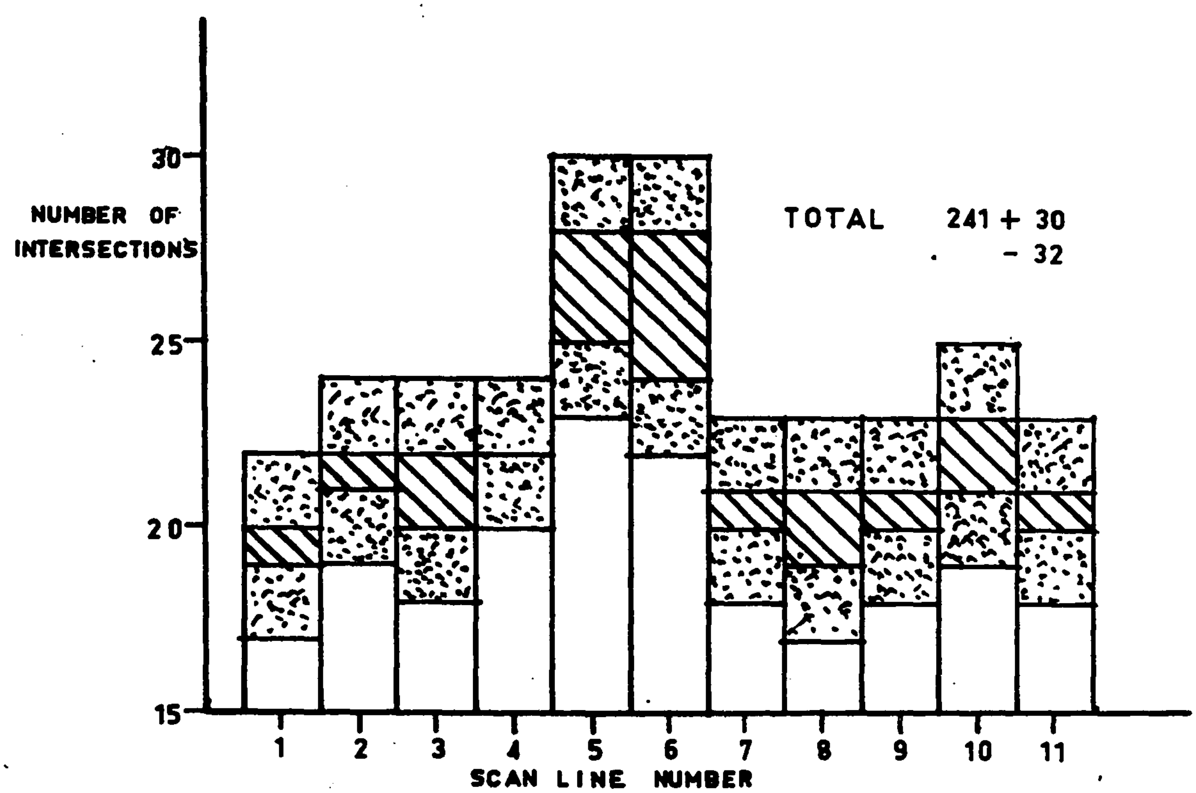


Figure 50, Histogram- Whorl

important, since the quasi-random number resulting from a scan depends on the number of ridges intersected and hence the alignment of the scan pattern. In essence, the line shaded error is an indicator of the repeatability of the scan. The error limits as shown in the histograms are based on an average ± 2% error found by the author when working with normal size fingerprints*.

The stipple shaded error is an indication of the irregularity in size and shape of the fingerprint based on the average difference found in observing different impressions of the same finger. Any one impression of a finger will exhibit either more or less total ridge area than any other impression of the same finger. Since Paolantonio's method depends heavily on the number of ridges intersected, and hence on how much print area is present, it is important to consider this error in the analysis. In effect, the amount of this error indicates the difficulty one would have in comparing a scene-of-crime impression with a good, filed impression of the same finger.

The amount of print area included or excluded depends on such things as: the pressure used in taking the fingerprint; the tone of the skin when the fingerprint is taken; the experience of the fingerprint technician; the type of ink and paper used; the surface upon which the paper is placed; the inking density; and the amount of cooperation given by the person who is being fingerprinted.

This impression error is estimated to be ± 10% of the dimensions of the fingerprint worked with, or on the average, about ± 2 ridges in terms of the fingerprints presently under investigation **

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* A 2% error is ± 0.02 inches on the average 1" x 1" fingerprint.
** This estimation is based on talks with the RCMP and the author's own observations.

Considering both types of errors, a worst case chi-squared test was made on the data, using the ulnar loop as the reference, or expected data. It was found that when using this test for the distributions of intersections (histograms), there was on the average only a 2% chance of all the fingerprints being different from an ulnar loop. Further, when a chi-squared test was made on the total number of intersections found in the fingerprint, rather than on the distribution of intersections, no difference amongst the fingerprints could be detected.

It may be argued that Paolantonio's method specified nine different scan patterns so that the results obtained are misleading. However, it is the author's contention that there are several more pressing problems than that of choosing nine scan patterns, and that these problems must be dealt with before the method of Paolantonio can be seriously considered as an automatic technique for classifying fingerprints.

For example, in the manual examination of this method, the scan pattern was arbitrarily placed so that it would cover the total fingerprint area presented. Since Paolantonio does not indicate otherwise, it may be considered that the placement of the scan pattern is arbitrary, and hence that the actual alignment of the pattern with respect to the fingerprint is unimportant. However, in carrying out multiple examinations of a single fingerprint using only one scan pattern, it was found that the major differences between the resulting quasi-random numbers was due to the fact that there was no reference with which the scan pattern could be aligned. Therefore this author feels that a reliable reference within the fingerprint has to be defined before this method can be used.

Another problem is that this method makes no distinctions as to which rotational configuration of a fingerprint should be used when making the analysis. This author found that different rotations of a fingerprint did generate slightly different quasi-random numbers, but that these numbers were insignificantly different if the errors mentioned before were considered. (See page 69.) Since the quasi-random numbers arising from the rotated analyses of one fingerprint were statistically equivalent to the quasi-random numbers generated by all the other unrotated fingerprints, it may be wise to confine the analysis to only one rotational presentation of a fingerprint. If only one rotational aspect of a fingerprint is to be used, then a two dimensional reference system has to be defined.

A further problem arises in trying to determine what a ridge is and how it is defined. If one uses noisy raw data, then the definition of a ridge is not simple. Time would have to be taken from the scanning operations in order to analyse every assumed ridge in order to see whether or not it is a ridge. Regardless of how one determines if a ridge is present, extra computer time is needed and this is costly.

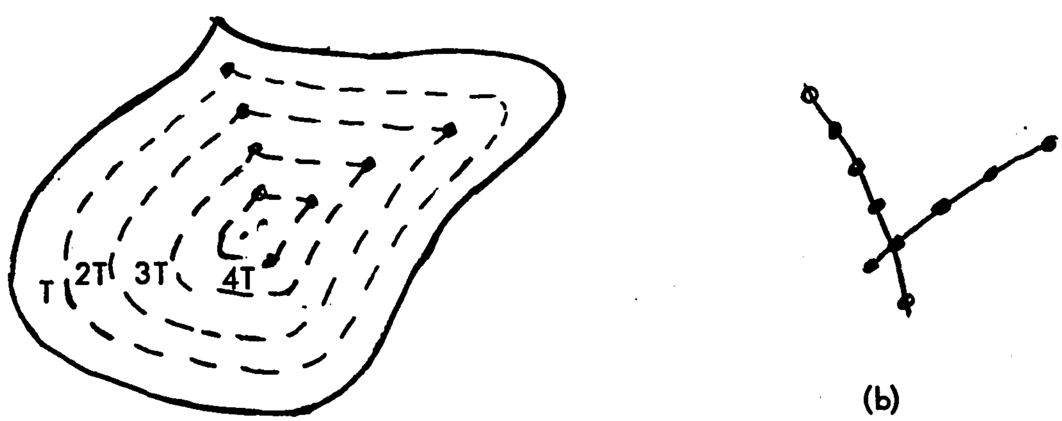
Finally as mentioned previously (page 73), there are differences in the total print area between multiple impressions of any fingerprint. This fact alone renders the method of Paolantonio unfeasible, since one cannot, with any degree of reliability or accuracy, define an arbitrary area in two or more impressions of the same finger, which will contain exactly the same information. To define such an area is a contradiction in terms. Therefore the author feels that further investigation into Paolantonio's method would be fruitless and that this technique cannot be effectively implemented on a computer.

5.3 The Method of Blum

Blum proposes a method of shape analysis[1] whereby a descriptor of a closed contour figure is extracted by a series of operations on the contour of the figure. The descriptor resulting from these operations is called the 'skeleton', or the 'medial axis transform'

(MAT)[26] of the figure. This author devised a method to analyse fingerprints which employs Blum's technique. It should be noted that the central theme of Blum's algorithm is the extraction of the skeleton from a figure.

One can generate the skeleton by what may best be described as the 'grass fire' method of wavefront propagation*. That is, consider the figure to be analysed to be made out of a homogeneous burnable material. One then sets fire to the boundary of the figure everywhere, simultaneously. As the fire burns through the figure, one notes that at some places, the fire will reach parts of the figure that have already been burnt out by the fire started from some other points on the boundary. Of one tabulates these points where the firetries to burn through itself, one obtains the skeleton of the figure. Figure 51 shows a



(a)
Figure

(b)
Extracted skeleton

Figure 51

a simple figure with Blum's method applied to it and the 'skeleton' extracted. Each interior contour represents the boundary of the fire at given times, T, 2T, 3T, and 4T if

* See also page 61 .

the fire is started at the boundary where $t = 0$.

Since a fingerprint is made up of many ridges, and thus has no single descriptive closed contour, one has to generate the most representative closed contour or 'super-contour' in order to apply Blum's method. The author decided to generate this super-contour, or average fingerprint by using the following rules:

(1) Starting anywhere in the print, follow five ridges at a time, replacing the five ridges by one ridge whose slope is the average slop of the five ridges, except where this contradicts rule 2.

(2) If any ridge of the five ridges being followed deviates from the average slope by more than a given minimum angle, eliminate those ridges from further operations with this group of ridges.

The rules for picking the super-contour from amongst the replacement ridges generated are:

(1) The super-contour shall be closed.

(2) The super-contour may if necessary follow the boundaries of the fingerprint.

(3) If rule 2 is employed, the super-contour that varies most rapidly and employs the least amount of boundary should be used.

These rules were applied to fingerprints B-5, B-6, and B-7 of Appendix B to generate the super contours in Figures 52 - 54 respectively. Blum's grass fire method was then applied to the super contours generating the skeletons in Figures 55 - 57. As can be seen, the arch and the tented arch skeletons have a marked similarity, whereas the radial loop skeleton is different from both of the other skeletons.

Blum's method does separate fingerprints into classes, but the question arises as to the resolution of the class structure. In using Blum's method, one has to generate an average fingerprint before one can begin analysis. This means one extra step of filtering (pre-filtering) and necessarily eliminates all of the fine structure (minutiae) of the print. Since a print is uniquely defined by these minutiae which Blum's method eliminates, one can consider the information derived from Blum's method only as a gross descriptor. Note however that the pre-filtering necessary would take a lot of effort and machine time whereas a technician can visually identify a fingerprint by its average or gross characteristics in under 10 seconds.

Since Blum's method generates only gross descriptors of a fingerprint, it will not be considered for computer implementation.

5.4 The Method of Rabinow Electronics

The Rabinow method for classifying fingerprints[28] has already been discussed in some detail (page 45) and will not be entirely restated here. The most important aspect of the Rabinow method is that it does make some attempt to define a reference point within a fingerprint. Since many researchers[6,25,36] consider the establishment of a reference system or reference point to be of prime importance in automated fingerprint analysis, the author chose to investigate that aspect of Rabinow's method which purports generating a

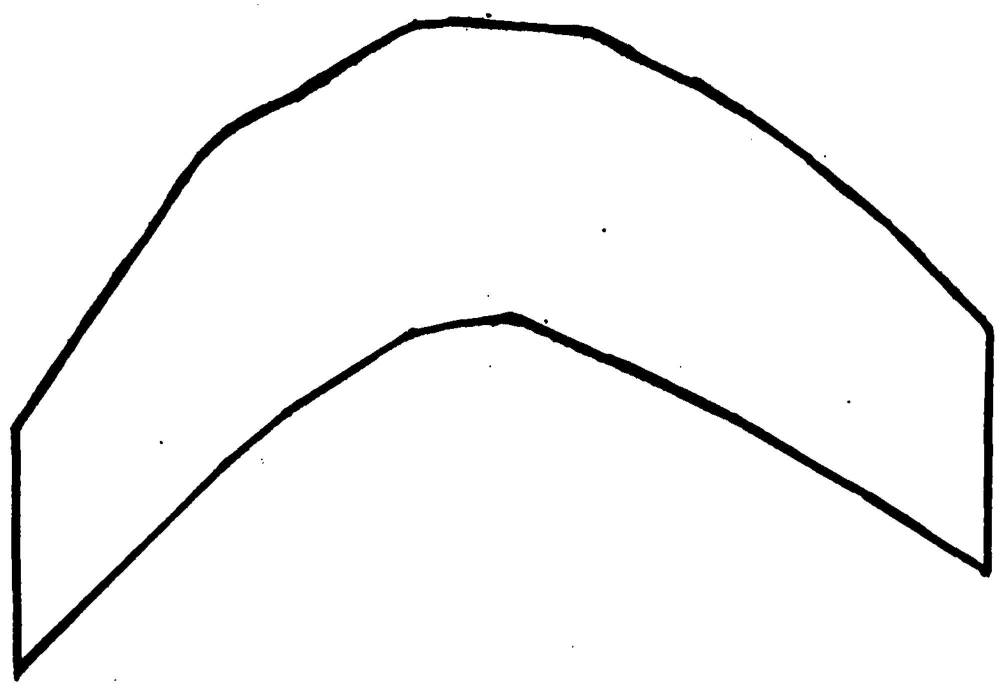


Figure 52 Average Arch

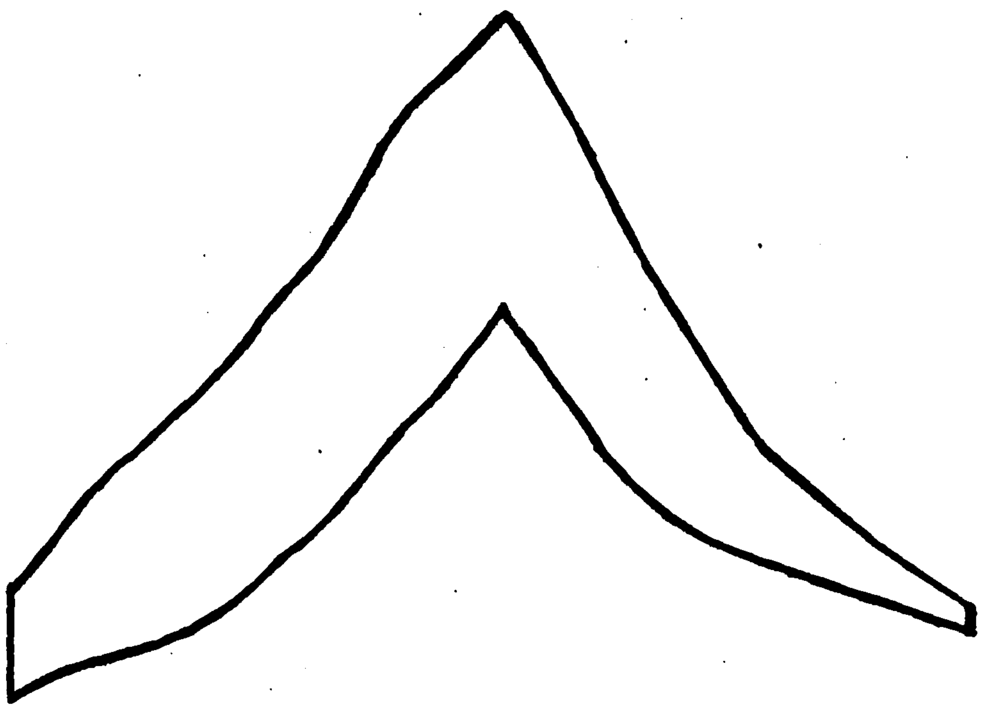


Figure 53 Average Tented Arch

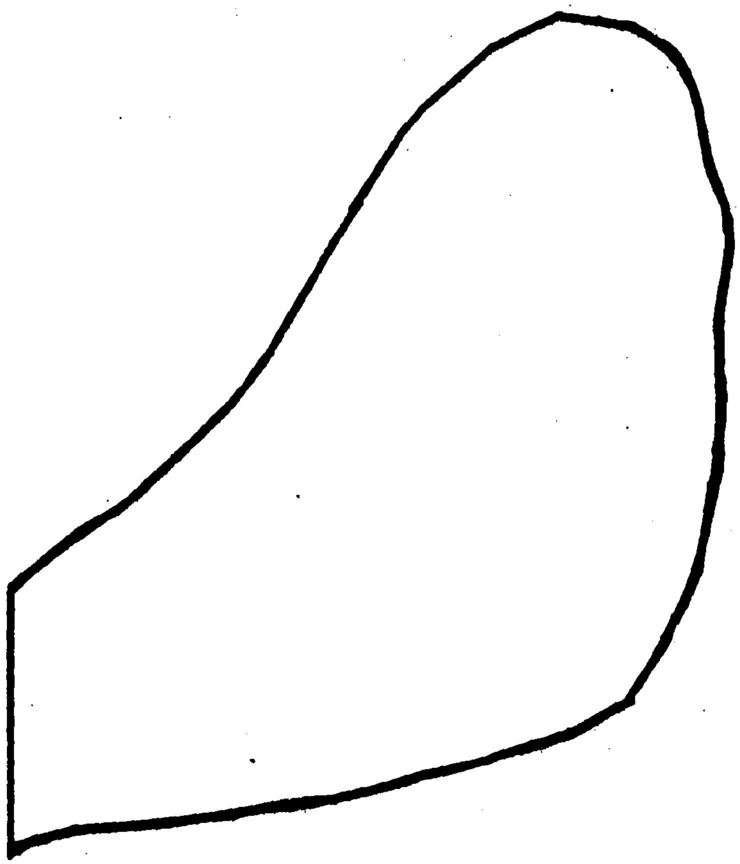


Figure 54   Average Radial Loop

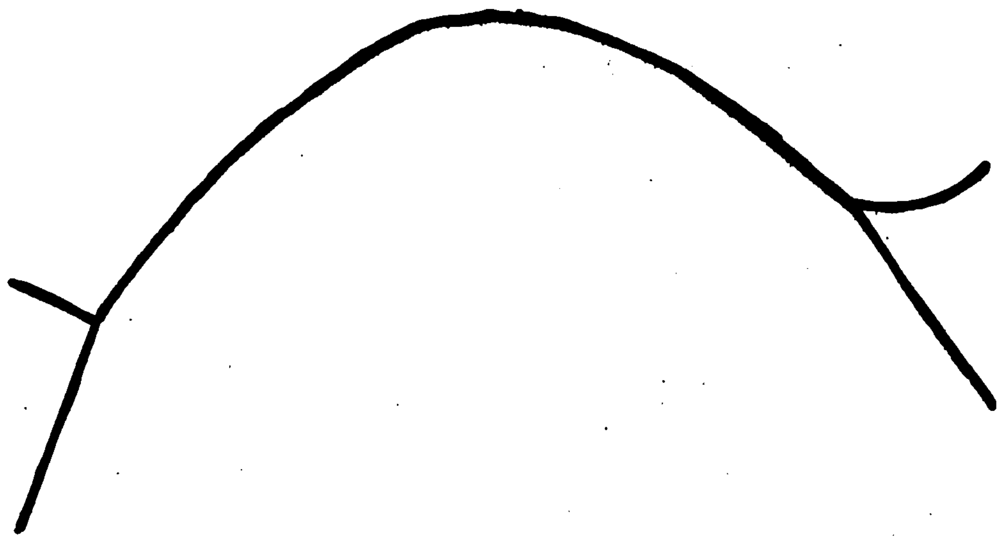


Figure 55 Arch Skeleton

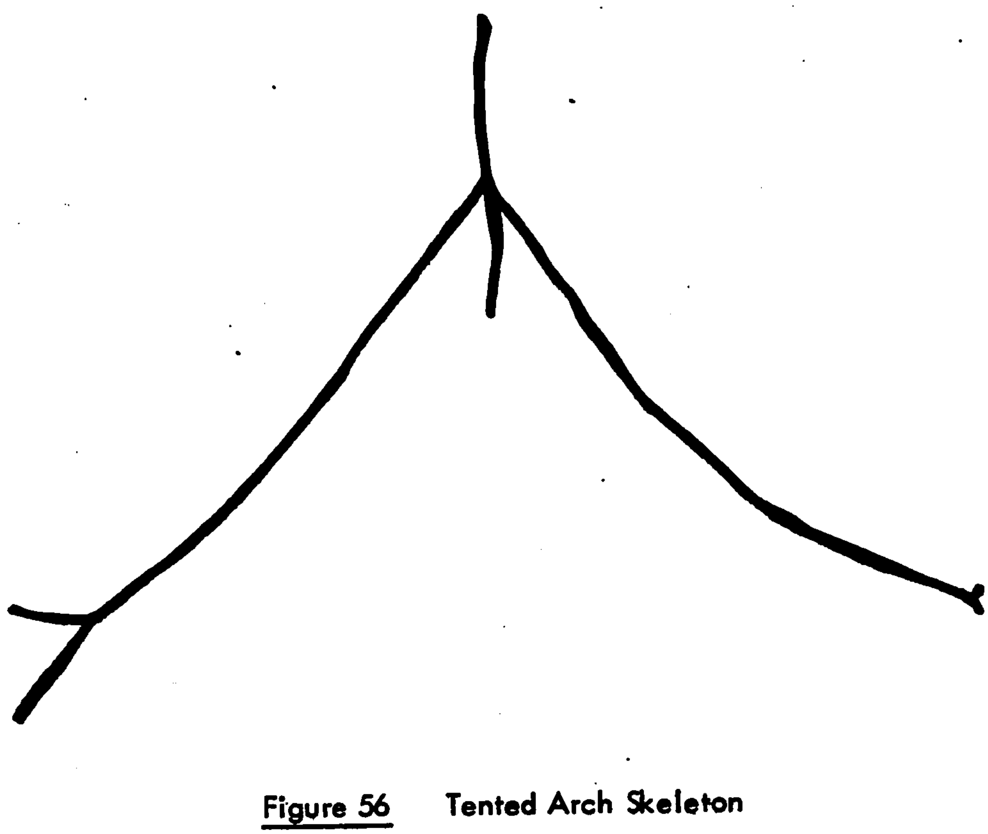


Figure 56 Tented Arch Skeleton

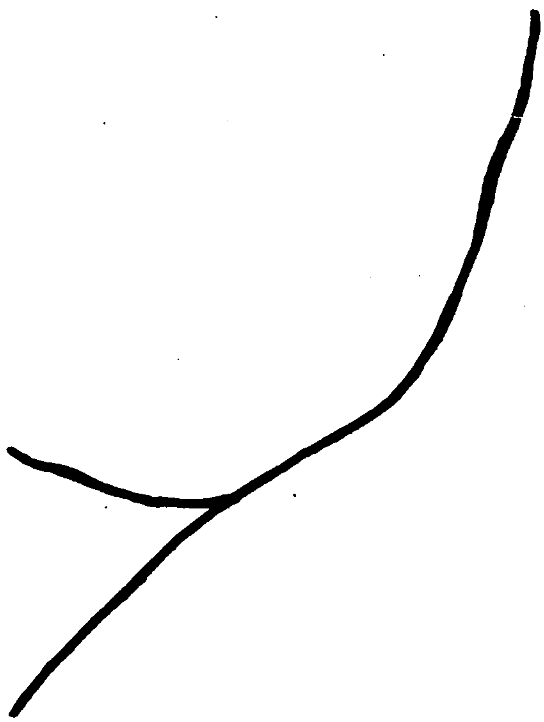


Figure 57   Radial Loop Skeleton

reference (central) point.

Rabinow uses analog methods (page 46) to generate trajectories in a fingerprint. A trajectory is any line that, starting from one point in the fingerprint moves to another point in the fingerprint, and is orthogonal to the ridge that it crosses. The orthogonality condition is the prime consideration in generating a trajectory. (Figure 58.) The portion

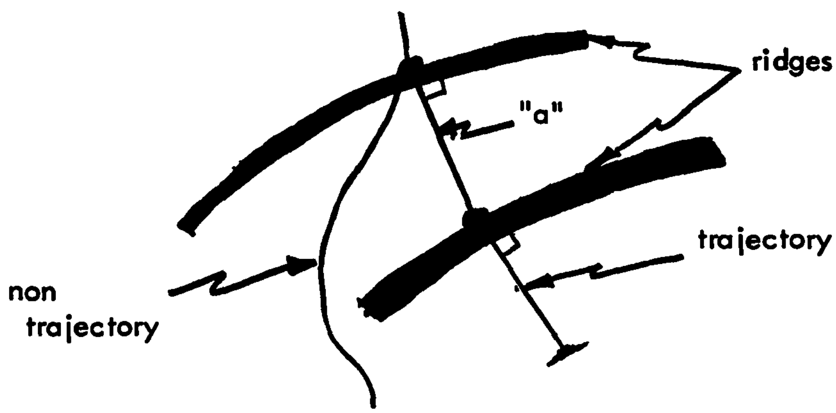


Figure 58 A Trajectory According to Rabinow

of the trajectory labelled 'a' in Figure 58 connects a point on one ridge to a point on the next ridge immediately following. Any such portion of a trajectory is called a trajectory segment.

In the actual analysis, an arbitrary number of trajectories (in the author's case, six trajectories are used) are initialized as equally spaced lines at the top of the finger-print, and are then made to travel throug. .ne print in the manner just described. The basis for using this trajectory analysis is Rabinow's observation that:

> "In any classification method, a system of coordinates must be established.... In a machine-oriented system is is more useful to define a point and a direction. This point could be the core of the present (Henry) system. However, all that is really required is that the point be the same on all prints of a given finger, and that the point be definable on a useful majority of fingerprints.

> One method of locating a point that satisfies the above requirements is to start a series of equally spaced vertical lines down from the top of the print. ..... Each time one of these lines reaches a ridge, the direction of the line is changed to make it perpendicular to the ridge. ...... it will be seen that all the lines intersect at an adequately definite (defined) point. ....." [28]

This intersection is defined as the reference point.

It can be seen from Rabinow's discussion that the orthogonal trajectory method is essentially a gradient technique for hill climbing. This is more evident if one considers the ridges of fingerprint as elevation contours of a hill. Rabinow has investigated the total method that it had proposed by testing it on fifty fingerprints. However, no indication was given as to how much research went into the defining and generation of a reference point.

The above mentioned trajectory analysis was applied manually to ten fingerprints and the results appear in Appendix C. It can be seen that a reference point was generated in each fingerprint. In some cases (for example, Figures C-2.1, C-2.2 and Figures C-9.1, C-9.2, C-9.3 and C-9.4), it was necessary to reduce the initial spacing of the trajectories in order to define a reference point.

Since it has been demonstrated that the manual analysis can effectively generate a reference point, the author has adapted this aspect of the method of Rabinow Electronics for a digital computer. A discussion of this digital method is presented in the next chapter.

CHAPTER VI

THE DIGITAL METHOD

6.1 Introduction

In this chapter the author presents a digital method for generating a reference point within a noise laden fingerprint. The digital method is a derivation from, rather than a direct simulation of, Rabinow's analogue method. However, in contradistinction to Rabinow's method, the digital algorithm does not employ any noise prefiltering techniques as part of the analysis, but rather attempts to analyse very noisy raw data. The digital algorithm was designed with this thought in mind: "Every operation that is not absolutely necessary to the final solution should be eliminated.". To this end, the author attempted to design an algorithm with enough flexibility to handle very noisy raw data, economically.

The digital method consists of two major parts, the Trajectory Analysis and the Intersection Analysis. The Trajectory Analysis is further split into the Slope Analysis and the Inter-ridge Travelling Analysis. The Slope Analysis examines a ridge in order to determine the average slope of that ridge in a small region. After analysing a ridge, the Slope Analysis gives the information obtained to the Trajectory Segment Generator (TSG) which then extends the trajectories through the fingerprint. The final operation is the Intersection Analysis which determines whether or not the trajectories have generated a reference point.

It must be remembered that the primary goal of this method is to generate the trajectories, since once the trajectories are generated, a common intersection (reference) point can be determined by visual examination of the analysis. At present the Intersection

Analysis is used to automatically extract the reference point, but this analysis is ineffectual as will be explained later. It is considered that if the reference points that are machine generated and extracted visually had been unique and repeatable, then a more comprehensive intersection analysis would have been designed. However, since it was found that the reference points are not unique, there is no benefit in producing a better intersection analysis.

6.2 A Digital Fingerprint

In order to clearly understand the algorithms that will be discussed, a few preliminary definitions and explanations are necessary. A fingerprint as seen by the computer is a 252 by 256 digitized array, four examples of which appear in Figures 59–62. The method and the equipment the author used for digitizing the fingerprints was developed by Reisch[29] for his research on the histology of the human lung.

As can be seen from Figures 59-62, the digitizing procedure converts all of the analogue information contained in a fingerprint into an 8-level grey code. The digital information is then converted from an 8-level grey code into a binary code, where every level greater than 3 is assigned the binary value 1, and is defined as black, while any level less than 4 is assigned the binary value 0 and is defined as white. In practice, any reference to the black areas of a fingerprint applies to the ridges, while any reference to the white areas of the fingerprint applies to the spaces between the ridges.

6.3 Reference System

In order to access various points within the binary fingerprint, the following reference system is adopted. (Figure 63.)

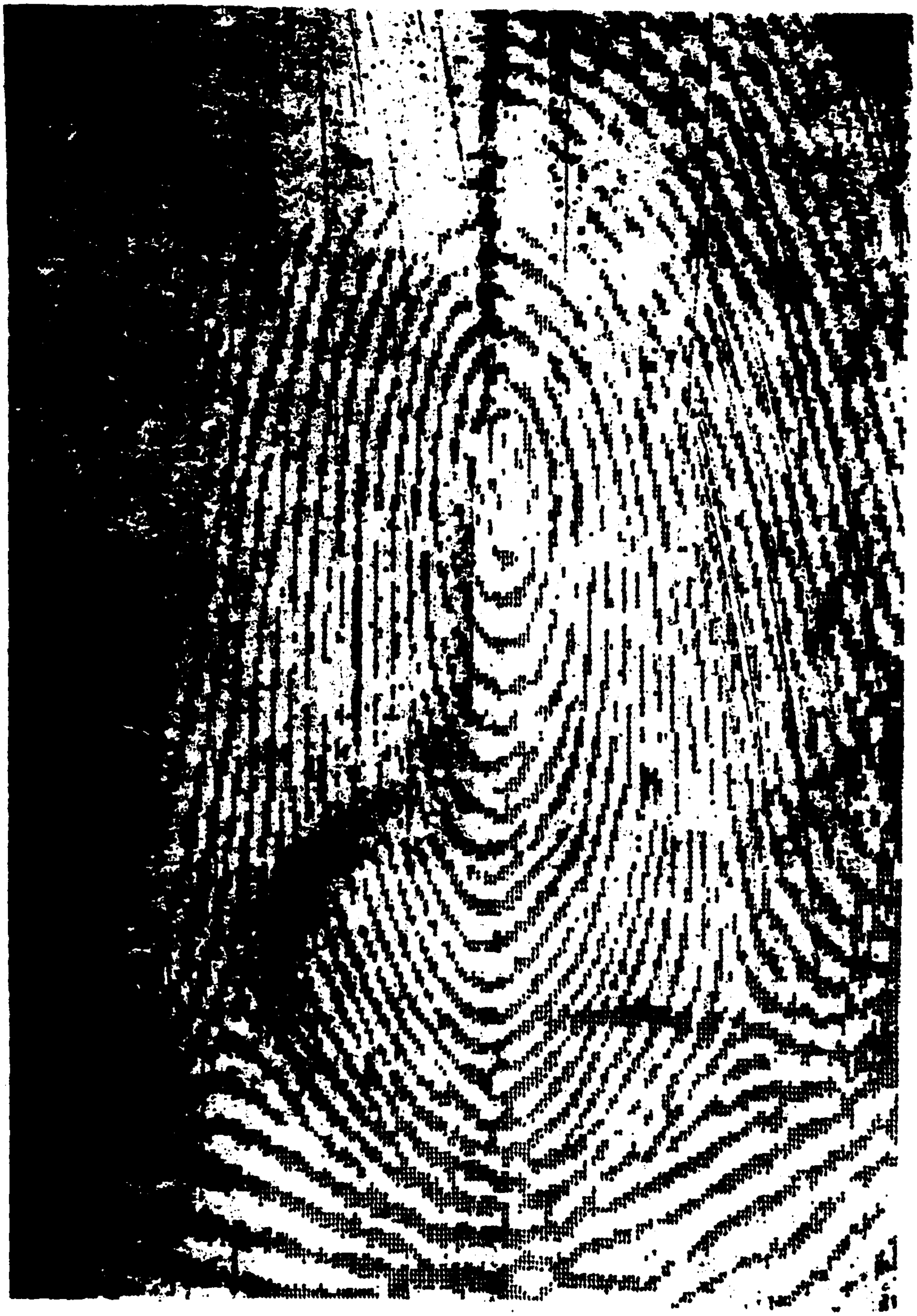


Figure 59 Digitized Fingerprint

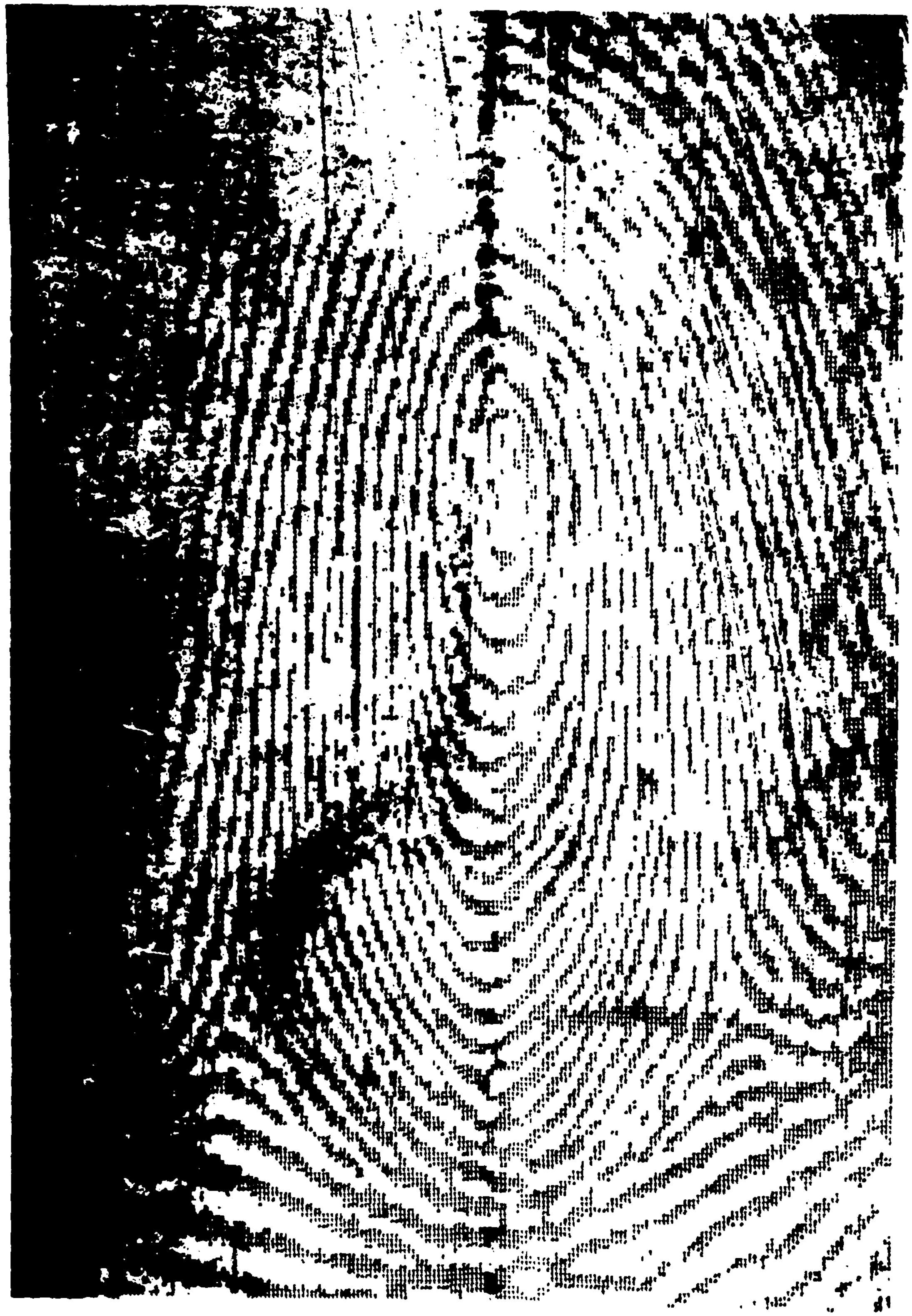


Figure 59 Digitized Fingerprint

Figure 60 Digitized Fingerprint

Figure 60 Digitized Fingerprint

Figure 61 Digitized Fingerprint

Figure 62 Digitized Fingerprint

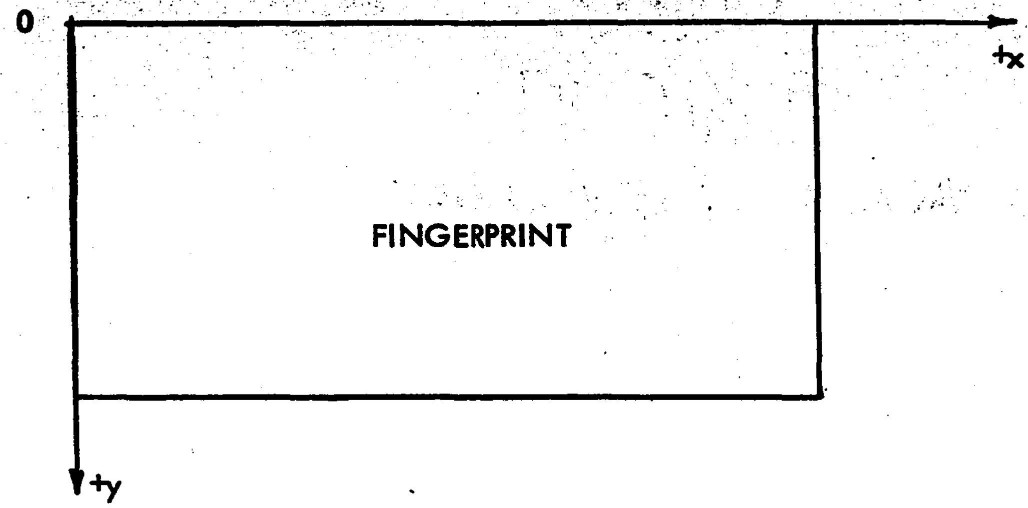


Figure 63 Reference System

The x-axis is aligned with the top of the fingerprint array, while the y-axis is aligned with the left hand border in the manner shown (Figure 63). Here, the top of the fingerprint is defined as that part of the impression resulting from the extremal part of the fingertip.

6.4 Initialization

The program's first duty is to initialize the trajectories in the fingerprint. This is done by the Master Processor which directs control to all the major analyses. Here, all six trajectories are initialized by equally spacing the starting points of the trajectories along the x-axis of the fingerprint. The field of search is defined as the euclidean distance between the starting points of trajectories 1 and 6. After the field is defined, all of the trajectories are forced to travel in the +y direction until each one finds a ridge (black) region within the fingerprint. (Figure 64.)

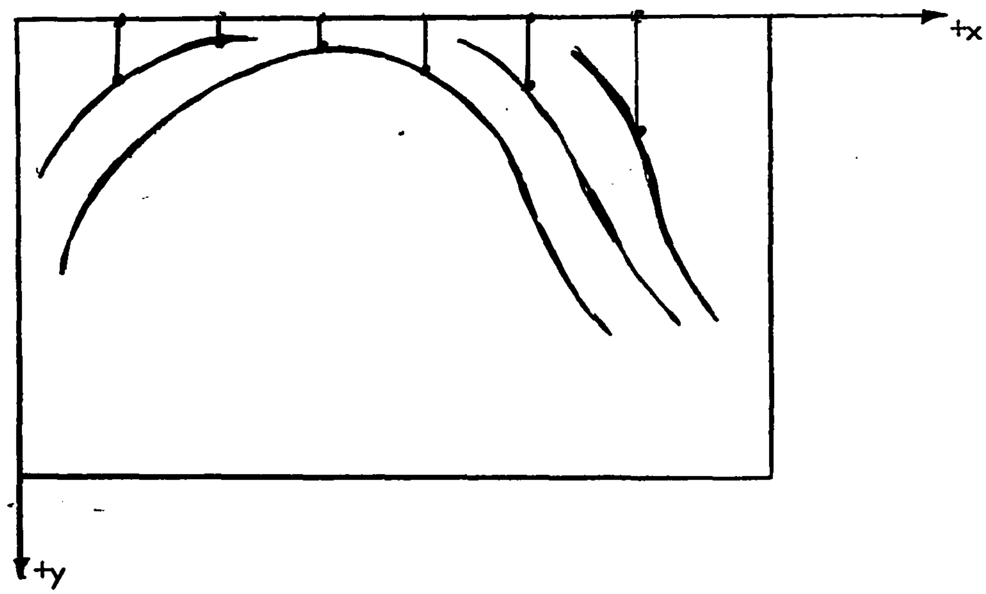


Figure 64 Trajectory Segments Generated by the Initialization Procedure

At this point the trajectory initialization is complete, and the Master Processor gives program control to the Slope Analysis. Figure 65 is an infomation flow chart illustrating the basic interactions amongst the algorithms about to be discussed.

6.5 Slope Analysis (SA)

The SA is the first analysis encountered after the trajectories are initialized. This analysis detemines the average slope and the orthogonal slope of a ridge in a given region of that ridge. To determine the average slope, a contour (ridge) following algorithm is employed. In order to follow a contour, the program must have the ability to make turns within the fingerprint. To this end, a Supervisor Program (SP) directs the contour following by means of a Generalized Right and Left Turning Algorithm (GRLA), and a Specialized Right and Left Turning Algorithm (SRLA). To understand the mechanics of these turning algorithms, one must first investigate the meaning of making a right or left turn with respect to moving within a digital fingerprint.

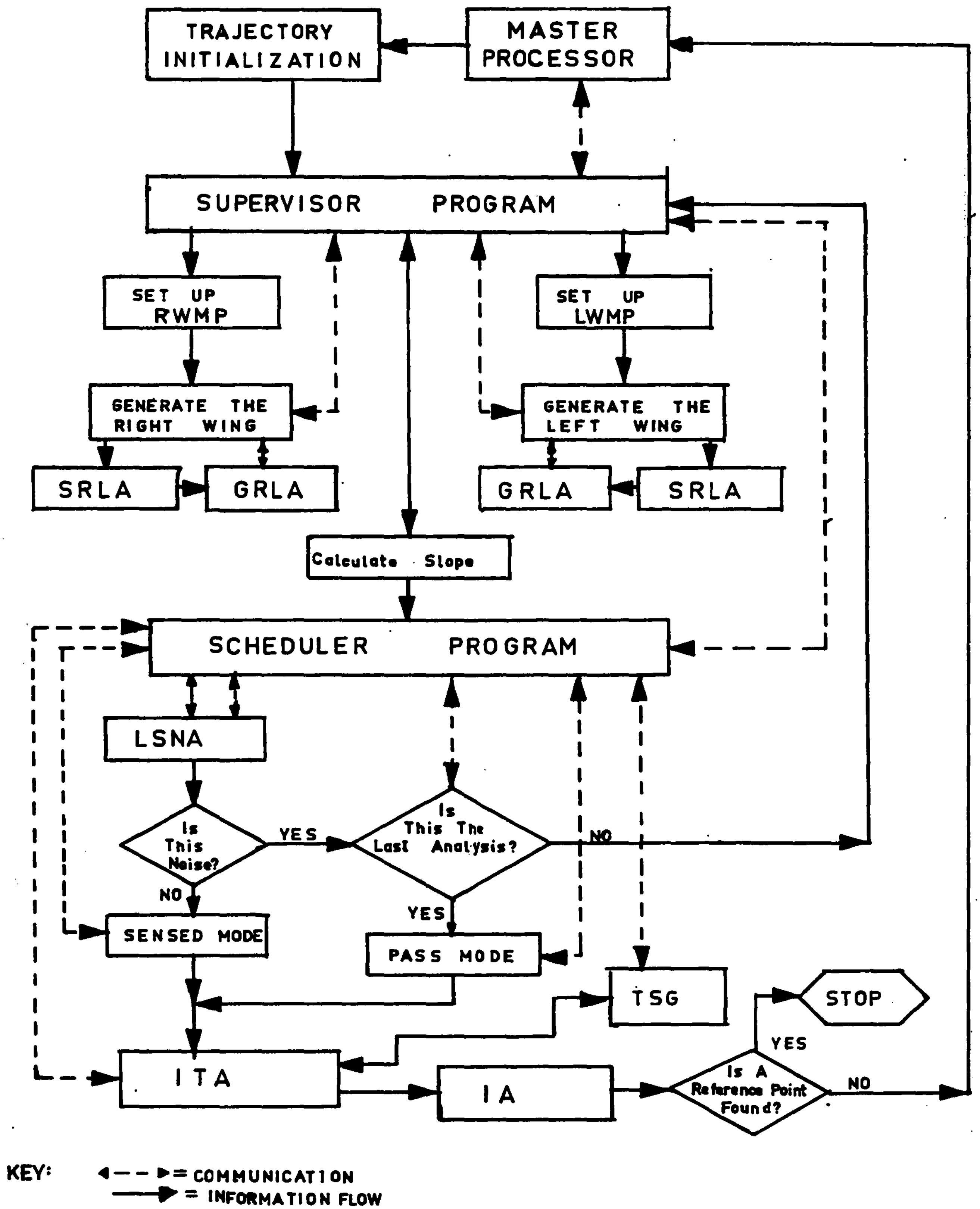


Figure: 65 Information Flow Chart

6.5.1 Nonspecific Turning

A nonspecific turn is defined as that turn which has a definite direction but an arbitrary magnitude. It is essentially a vector of undefined magnitude. The best way to visualize the nonspecific turns that are used in defining specific turns (see Section 6.5.2) for the contour following algorithms, is to imagine that you are walking along a trajectory in its direction of travel. (See Figure 66.)

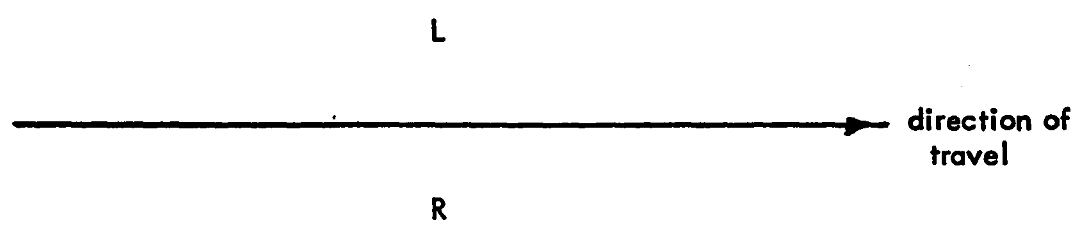
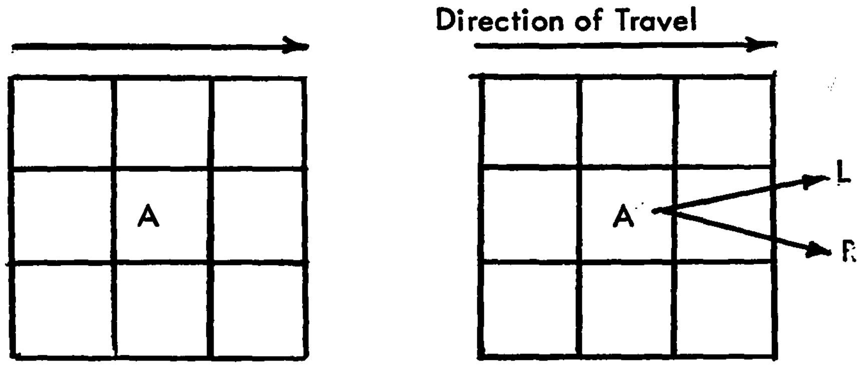


Figure 66 Nonspecific Right and Left Turns

Here a nonspecific right turn can be made to any point in the half plane on one's right side (R in Figure 66), while a nonspecific left turn can be made to any point on one's left side (L in Figure 66). Note that the nonspecific turns are allowed to be in the forward direction as well as in the reverse direction of travel. This is so by virtue of the fact that in defining a direction in a digital picture, one has only discrete points to which one can move. Therefore, if the resolution of the digital grid is coarser than the resolution used to define the analogue right and left turns, then both a right and left turn may be to the same digital point. This can be seen more clearly in light of the definition of specific turns.

6.5.2 Specific Turning

Consider the typical 3 by 3 grid (Figure 67a), that represents the neighborhood of the point A in a digital array. Now a specific turn from point A is defined as that turn



(a) Neighborhood of Point A

(b) Nonspecific Right (R) and Left (L) Turns

(c) Specific Right and Left Turn from A to B

Figure 67

which is made to one of the points of the grid in the neighborhood of point A. Consider that a nonspecific right and left turn has been determined to be in the R and L directions (Figure 67b) respectively. In order to make such turns in a digital array (specific turns), the closest digital approximation to each of these directions in the neighborhood of A has to be determined.

In this case, the turn to point B from point A (Figure 67c) is the closest digital direction to both of the nonspecific turn directions. Hence, the specific right and left turns from point A can be made to point B, which point is in the direction of travel. Since specific turns are defined in relation to nonspecific turns in the above manner (for the SRLA only), it is necessary that the direction defined for nonspecific turns be allowed to overlap. A similar argument holds for specific turns made to a point directly opposite to the direction of travel.

With the above in mind, one can now examine the algorithms that direct the specific turns needed for the contour following.

6.5.2.1 Specialized Right and Left Turning Algorithm (SRLA)

The SRLA is only used immediately after a trajectory has arrived upon a ridge, and as such is the first algorithm to be encountered after the trajectory initialization and upon entering the Slope Analysis. Consider the 3 x 3 grid shown in Figure 68.

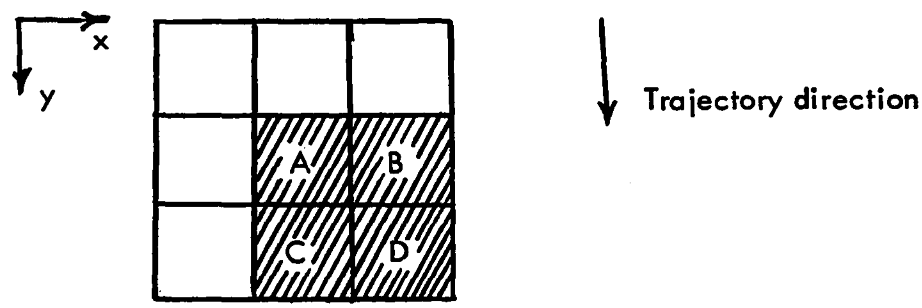
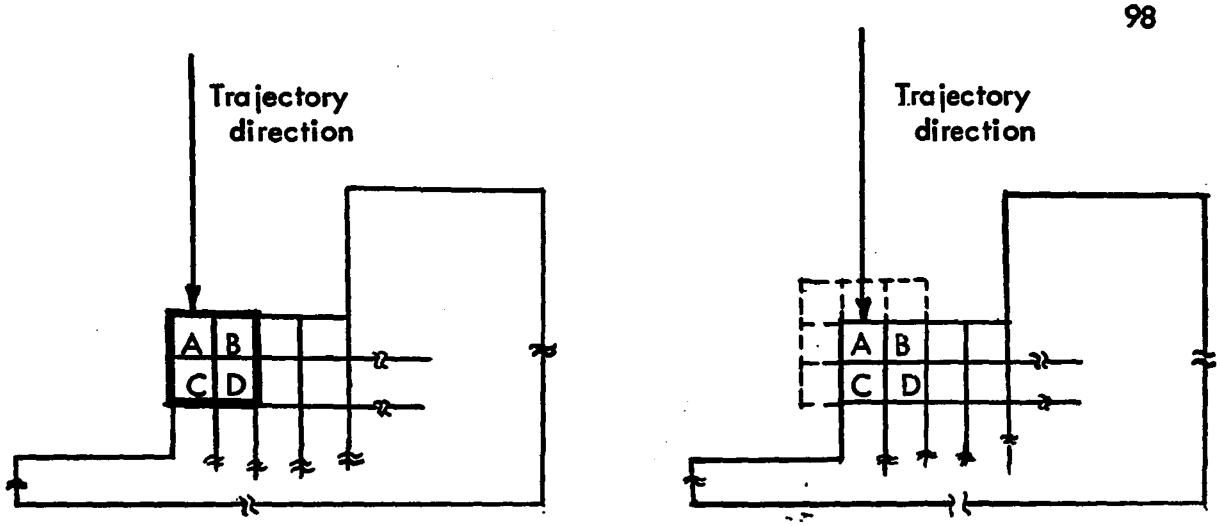


Figure 68 Ridge Region in Neighborhood of Trajectory End Point A

Points A, B, C and D are black or ridge points, while the unlabelled points in the neighborhood of A are part of the inter-ridge spaces. Here, point A is the point on the ridge that the trajectory has arrived at. Seen in a larger context, Figure 68 may appear as in Figure 69. Now, since the Supervisor Program demands that contour following be initiated, it is the job of the SRLA to pick the best initial right and left turns. In order to determine what a specific right and left turn from point A is, the SRLA has to have information about all of the points in the neighborhood of point A, and as well, know the trajectory's direction of travel. Using the concept of a nonspecific right and left turn, the SRLA examines the neighborhood of point A in order to determine specific



(a) Ridge Region with Ridge Points of Figure 68 Highlighted

(b) Ridge Region with Figure 68 Superimposed

Figure 69

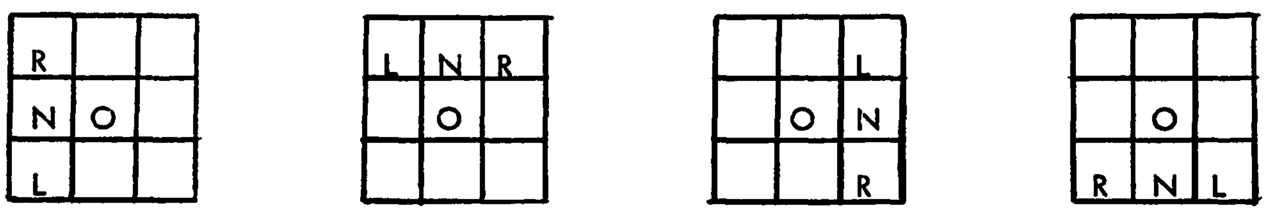
right and left turns. In the case of Figures 68 or 69, the best right and left turns from point A are determined to be to points C and B respectively. The term specialized Right and Left Turning Algorithm comes from the facts that: first, the SRLA examines the neighborhood of a point before deciding upon the best right and left turns; and second, the SRLA is used only once each time the Slope Analysis is called to examine a trajectory. In contrast to the SRLA, the GRLA is used for making all turns during the contour following operations, and does not use information about the neighborhood properties of a point.

6.5.2.2 The Generalized Right and Left Turning Algorithm (GRLA)

After the SRLA has determined the best right and left turns, the Supervisor Program passes this information to the GRLA which is the next algorithm to be used. The only information that the GRLA needs in order to determine how to make a turn is the coordinates of the present or new point, the coordinates of the previous or old point and whether a right or left turn is desired. The information about the points is initially passed to the GRLA by the SRLA as in the case of Figures 68 or 69, where the coordinates of point A (Figures 68, 69) are passed as the coordinates of the previous point, and the coordinates of C or B are passed as the coordinates of the present point depending on which points (AC or AB) the Supervisor is working with. Thereafter the GRLA generates its own information about the coordinates of the two points needed while the Supervisor Program injects information about the type of turn desired - either right or left.

The term Generalized Right and Left Turning Algorithm derives from the fact that the algorithm does not use information about a neighborhood of a point to determine a turning direction. Instead the GRLA uses an ordered set of two points, which is the least amount of information needed to determine a direction in a euclidean two space. Finally the GRLA is independent of the trajectory's direction of travel.

Figure 70 shows the various turns that the GRLA makes. Note the only



(a) (b) (c) (d)

Legend:

O = old or previous point

N = new or present point

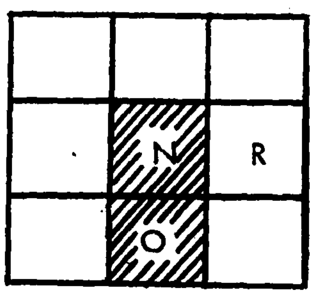
R = right turn as determined by the GRLA

L = left turn as determined by the GRLA

Figure 70 Right and Left Turns Made by the GRLA cases considered by the GRLA involve right angle turns. By considering only these cases, the GRLA can be directed by the supervisor to use the contour following algorithm devised by Mason and Klemens[15] and adapted for a digital machine by the author. Further this definition of turns reduces the number of cases one has to otherwise consider, and thus increases the efficiency of the GRLA in terms of machine execution time.

6.6 The Supervisor Program (SP)

The main job of the Supervisor is to carry out the contour following on the ridge by directing the SRLA and the GRLA through a certain number of color crossings. A color crossing occurs when either the SRLA or the GRLA makes a turn from an initial point and finds a new point with a different color than the initial point. Figure 71 shows a black to white color crossing upon taking a right turn. In order to follow a ridge,



Legend:

O = old point

N = new point

R = right turn made by GRLA

black region

Figure 71 Black to White Color Crossing

the supervisor determines whether or not a crossing is made and then instructs the GRLA to take the next turn in the appropriate direction. The way in which this directions is chosen can best be understood in terms of Figure 72.

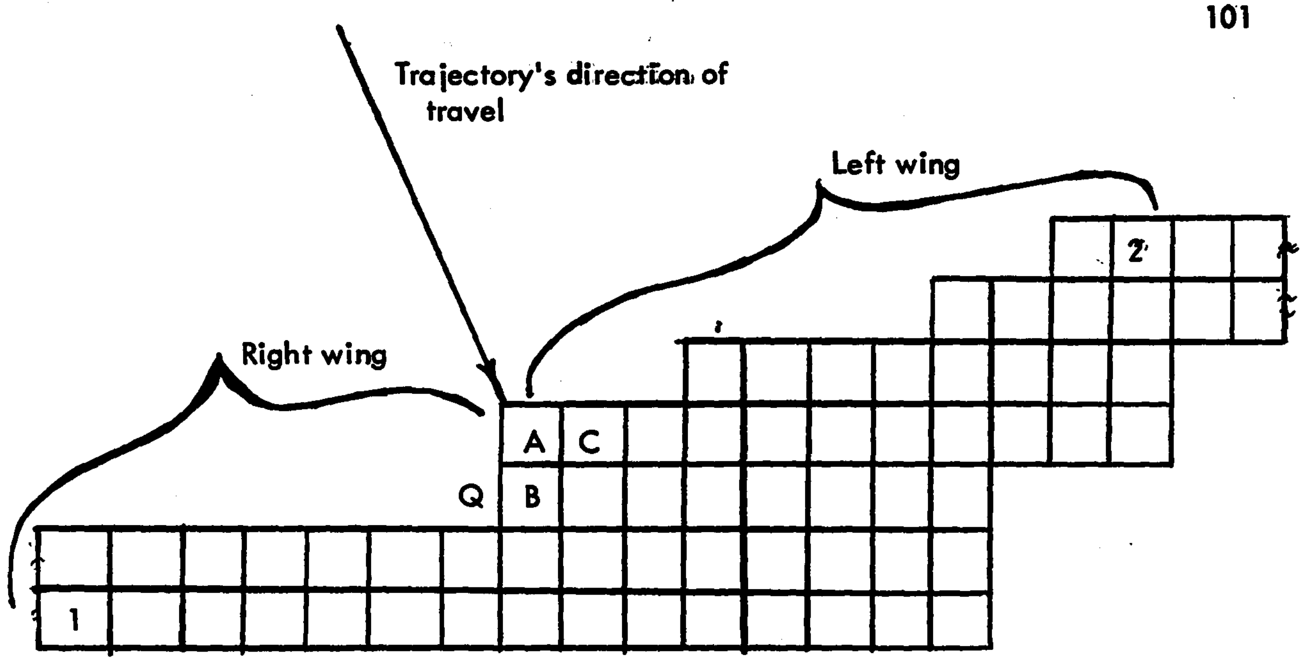


Figure 72. Typical Digitized Ridge

Point A (Figure 72) lies on a ridge which has been found by either the trajectory initialization procedure or by the Inter-ridge Travelling Analysis. The SRLA has chosen points B and C to be, respectively, the best initial right and left turns from point 'A'. At this point, the Supervisor Program chooses the right wing to work on, where the right wing is that part of the ridge which is in the direction of the initial right turn chosen by the SRLA. A similar definition follows for the left wing.

The SP then directs the GRLA to look at the points A and B as the old and new points respectively (Figure 72) preparatory to making a turn. The procedure by which the SP decides whether a right or left turn should be made when working in the right wing is called the Right Wing Main Proposition of the contour follower (RWMP) which is stated as follows: when working on the right wing, make a right turn each time the new point is black and a left turn each time the new point is white. In Figure 72, A is taken as the old point, B is taken as the new point and according to the GRLA and the RWMP,

(Figure 70d) the right turn is made to point Q. Now, preparatory to making the next turn, the GRLA takes the last new point (B) and makes it the old point. Next the GRLA makes the point just arrived at (Q) the new point. At this time, the Supervisor Program examines the color of the new point (Q) and decides which way to make the next turn according to the RWMP.

The Supervisor and GRLA continue to interact in this manner until a prescribed, albeit arbitrary number of color crossings have been made. The author found that ten color crossings in each wing was sufficient to determine the average slope of a ridge within the region of point A for all the fingerprints examined even though no excessive care was taken to ensure constancy of ridge detail, ridge noise, or magnification factor amongst the prints. Further, the author used a range of 6 - 16 allowed color crossings per wing for several fingerprints and found no appreciable difference in the total analysis.

By generating the desired number of color crossings, the Supervisor arrives at a point such as point 1 in Figure 72. After noting the coordinates of this point, the Supervisor proceeds to work on the left wing by using the Left Wing Main Proposition of the contour follower (LWMP) which is: when working on the left wing, make a left turn each time the new point is black and a right turn each time the new point is white. The Supervisor uses the LWMP as it used the RWMP and eventually arrives at point 2 (Figure 72) and stores point 2's coordinates. When the Supervisor has the coordinates of both points (1 and 2), it calculates the slope as

$$m = \frac{\Delta Y}{\Delta x} = \frac{Y_1 - Y_2}{x_1 - x_2}$$

and the orthogonal slope as

$$\omega = -\frac{1}{m}$$

and stores them for use later on in the program. Finally, the Supervisor examines the other trajectories in a similar manner, and upon completing this task passes control of the analysis to the Scheduler of the Inter-Ridge Travelling Analysis.

6.7 Inter-Ridge Travelling Analysis (ITA)

The purpose of the ITA is to extend a given trajectory by one segment in a given direction. This direction is determined by the Schedules of the ITA and the Large Scale Noise Algorithm in conjunction with the information derived from the Slope Analysis.

6.7.1 Large Scale Noise Algorithm (LSNA)

Upon receiving control from the Supervisor of the Slope Analysis, the Scheduler of the ITA directs the LSNA to conduct its analysis. Basically, the LSNA tries to determine whether or not the black regions the slope analysis has worked with are ridge fragments or ridges. (See Figure 73.)

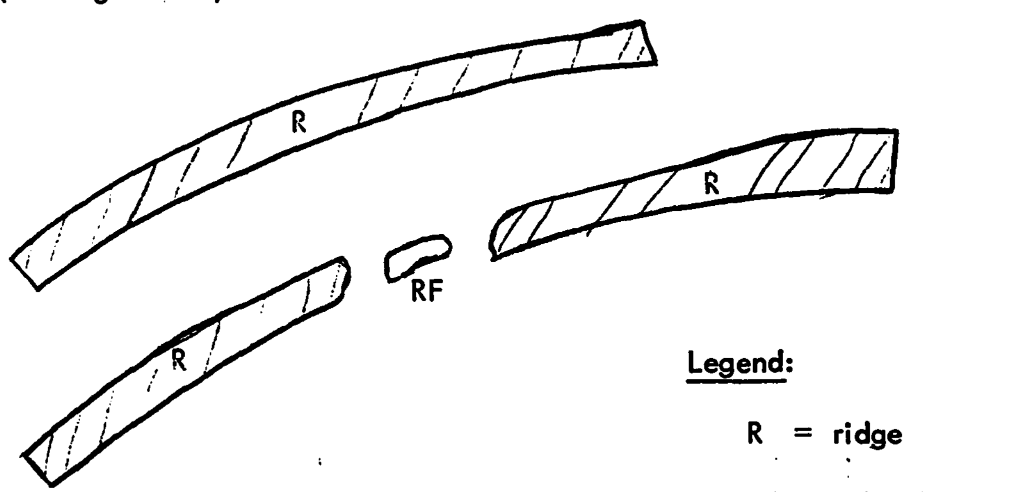
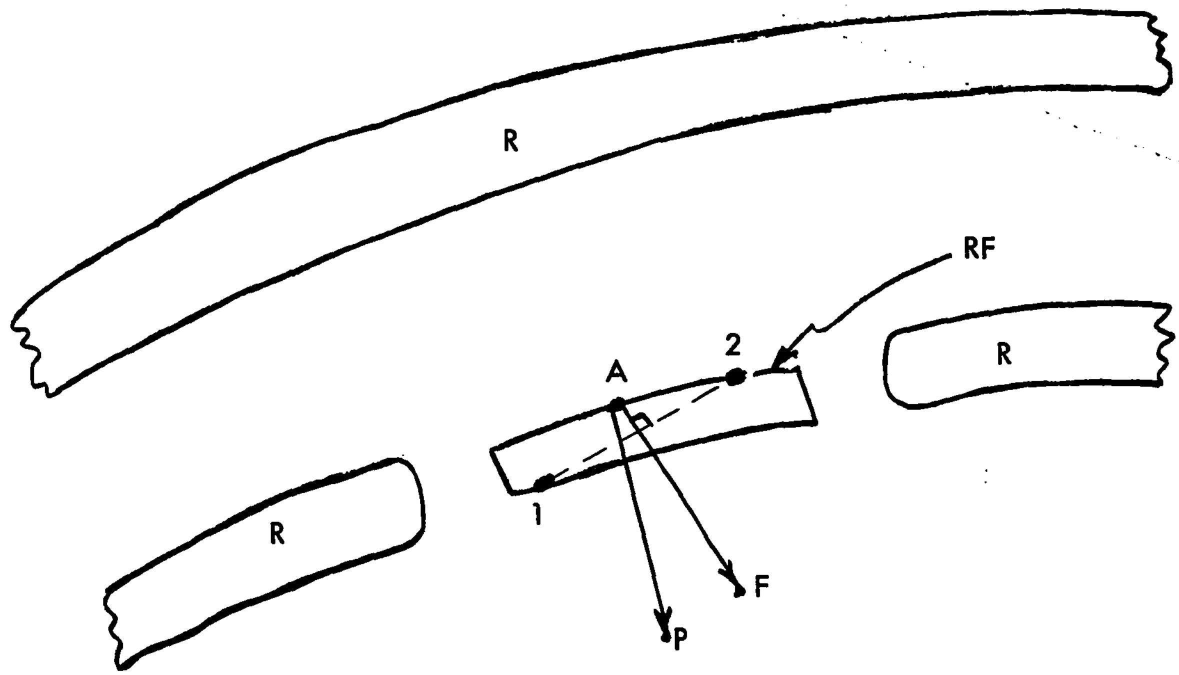


Figure 73 Idealized Representation of Ridges and a Ridge Fragment

It must be stressed that (Figure 73) is an idealized physical representation of ridges and a ridge fragment. In practice a ridge fragment is operationally defined in a manner to be given shortly. If the LSNA determines that the black area is a ridge fragment, then the possibility exists that the slope determined by the SA is spurious. The reason for this can be seen by considering Figure 74.



Legend:

R	=	ridge
RF	=	ridge fragment
A,1,2	=	points defined in contour following
AP	=	"correct" orthogonal line
AF	=	"spurious" orthogonal line found from slope of 12

Figure 74 Ridge and Ridge Fragment

In this case, the SA will determine the slope of the line defined by points 1 and 2. Accordingly, the orthogonal slope is determined to be defined by the line $\underline{AF}$, whereas if the ridge fragment were considered in the context of the ridges around it (R), the orthogonal slope would be defined by the line $\underline{AP}$. It is this latter orthogonal direction (AP) that one would like to find regardless of whether one lands on a ridge or a ridge fragment, but in the interests of an economical use of computer time, one would like to find the line AP without using a full contextual analysis of the region. In an attempt to determine the orthogonal slope by using only the SA, and as such, rejecting contextual analysis, the LSNA makes a simple threshold comparison between the number of color crossings made, versus the euclidean distance $\underline{A1}$ and $\underline{A2}$. Here the number of color crossings is used as a crude approximation to the actual distance travelled along a wing.

Figure 75 presents a magnification of the idealized ridge fragment shown in Figure 73 with the points A, 1 and 2 as initially determined by the Slope Analysis. Now

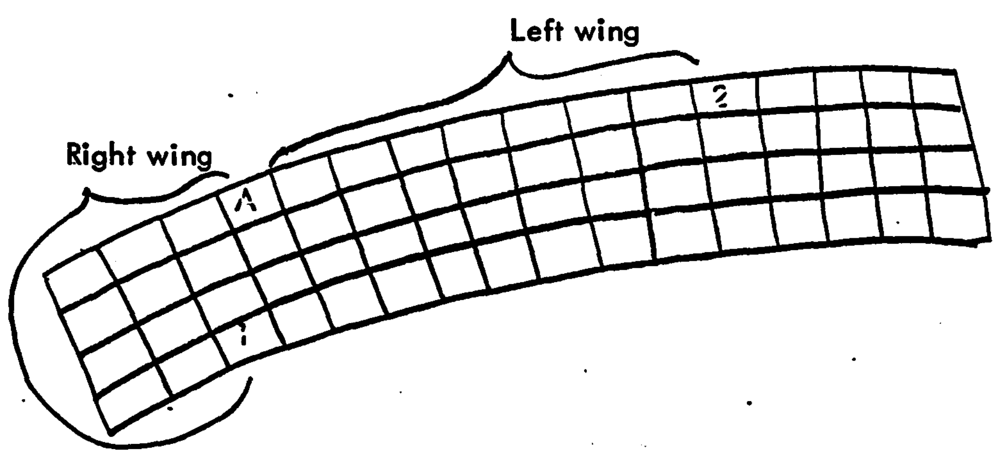


Figure 75 Idealized Ridge Fragment

the LSNA makes the following two comparisons:

$$\text{(i)} \qquad \frac{\text{No. color crossings in right wing}}{\overline{A1}} \overset{?}{\leq} 2.5$$

and

$$\text{(ii)} \qquad \frac{\text{No. color crossings in left wing}}{\overline{A2}} \overset{?}{\leq} 2.5$$

where $C \overset{?}{\leq} D$ means "is $C \leq D$?" These comparisons are used as indications of how much a wing has curved back on itself. If either of the comparisons are true, the slope as determined by the SA is discarded since it is considered to be spurious. The number 2.5 as used in the comparisons is arbitrarily chosen. However, in actual analyses, this value (2.5) is found to work rather well as a threshold value for the LSNA. Note it is this threshold comparison that is used to operationally define a ridge fragment.

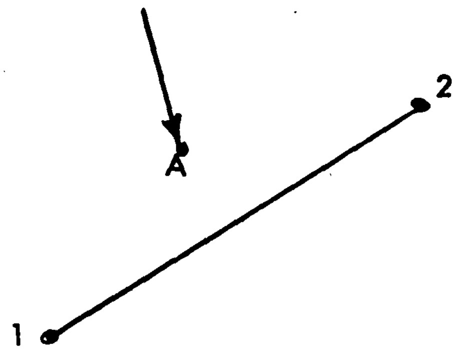
When a slope is discarded, the Scheduler informs the Supervisor Program of the Slope Analysis, and then waits until the Supervisor signals that another Slope Analysis has been made preparatory to reinitiating the LSNA. This further Slope Analysis is made with the number of required color crossings reduced by 2 for the wing or wings that failed to meet the threshold criterion. If, for these further analyses, the required number of color crossings is reduced past the value 6, then the Slope Analysis is aborted and the Scheduler uses the Pass Mode(see Section 6.7.2) of inter-ridge travelling for this segment of the trajectory. The reason for aborting the Slope Analysis is that, for values of 4 or less required color crossings, there is on the average too much small scale ridge noise to allow for a reliable estimation of the slope.

There are two ways for the interplay amongst the Scheduler, Supervisor, LSNA, and SA to terminate. The first, which has already been mentioned, occurs when the number of required color crossings has been reduced to 6 or less. The second type of termination occurs when the LSNA interprets the black area under examination as a ridge rather than a ridge fragment. If this type of termination occurs, the LSNA advises the Scheduler to use the Sensed Mode (see Section 6.7.1) of travel in order to generate the next segment of this trajectory. The Scheduler notes this recommendation and then proceeds with a similar LSNA analysis for the rest of the trajectories. When the complete LSNA analysis of all trajectories is finished, the Scheduler directs control to either the Sensed Mode or Pass Mode of the Trajectory Segment Generator (TSG). The TSG then extends the trajectory further into the fingerprint.

6.8 Trajectory Segment Generator (TSG)

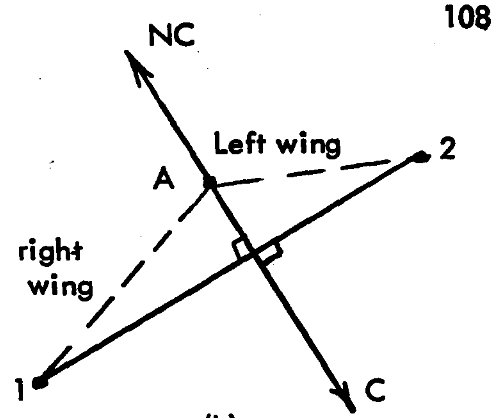
6.8.1 Sensed Travel Mode (STM)

The term sensed mode of travel is derived from the ability of the algorithm to sense the correct orthogonal travelling direction by considering past information about the trajectory's direction of travel and other information generated by the Slope Analysis. It can be seen from Figure 76b that there are two directions (C and NC) one could move in and still be orthogonal to the slope determined by the Slope Analysis. To determine which of the orthogonal directions is best, the sensed mode uses the original meaning of rightness and leftness as previously defined in Section 6.5.1.



(a)

Travel Direction of Trajectory to Point A



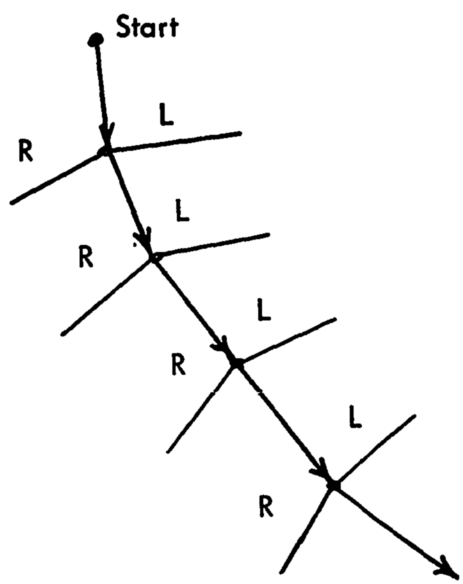
(b)

Orthogonal Directions (C and NC) to a Given Line (12) in Figure 76a

Key: A, 1, 2, are the points defined by SA

Figure 76

With this definition implemented, the best orthogonal direction of travel, as determined by the sensed mode, is chosen to be in that direction which keeps the right wing on the right side of the trajectory and the left wing on the left side of the trajectory. Figure 77 schematically presents this concept in terms of one trajectory. One important



Key:

R = right wing

L = left wing

Figure 77 Trajectory Generation Using the Sensed Mode point is that the definition of rightness and leftness as used by the Sensed Mode is not the sole arbitrator in determining the final direction of travel, for by using only the Sensed Mode method of determining the direction, one could theoretically travel in circles (Figure 78).

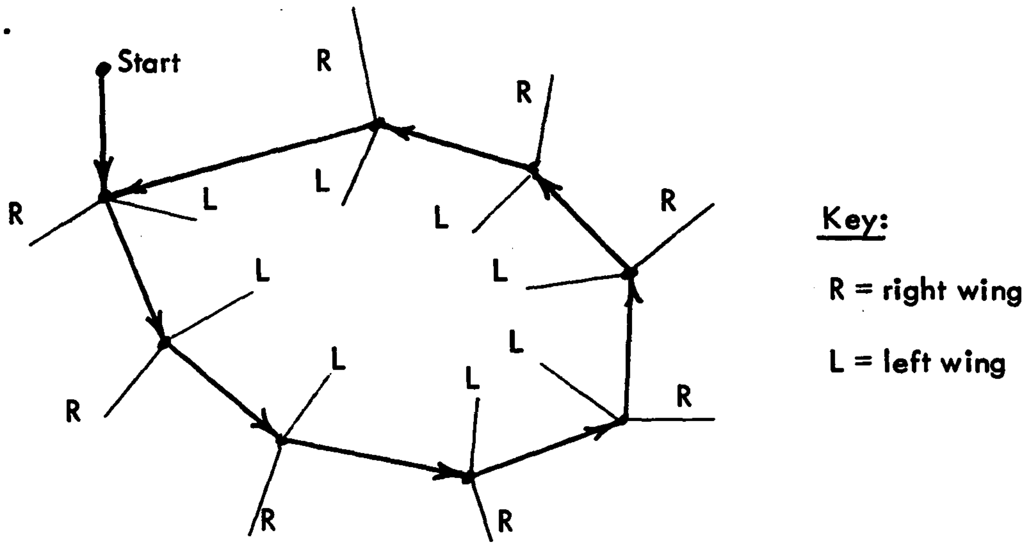


Figure 78 Circular Travelling Using Only the Sensed Mode of Travel

In order to make sure that the trajectory does not travel in circles, the Scheduler examines the direction determined by the sensed mode in light of the travel direction chosen n steps ago. Here n is a delay factor which in theory is arbitrary, but in practice was chosen to be in the range from 1 to 5. This range allows one to consider such factors as the ridge spacing and the magnification factor of the fingerprint. Although n is arbitrary, the author found that n = 3 allowed for a cogent analysis of all the fingerprints examined.

After the direction of travel is totally determined, the Scheduler instructs the Travelling Algorithm to generate the next segment of the trajectory. After the segment is generated, the Scheduler commences analysis on the next trajectory.

6.8.2 Pass Travel Mode (PTM)

The PTM is used only when a Sensed Travel Mode cannot be determined. The name Pass Travel Mode derives from the fact that the Scheduler instructs the Travelling Algorithm to use the last determined direction of travel for the trajectory in order to generate a new trajectory segment. In this way, the PTM allows a trajectory to keep on travelling in the correct general direction regardless of the ridge conditions encountered.

6.8.3 Travelling Algorithm (TA)

The Travelling Algorithm is the physical generator of the trajectories. The TA digitally extends a trajectory by one segment, across the face of the fingerprint, using information about ridge conditions and travel direction, that is fed to it by the Scheduler. The travel direction as used by the TA is the best digital approximation to the analogue direction determined by the Scheduler. The methods employed for determining the digital direction are derived from Freeman's work[8,9,10] on digital geometric line patterns.

Basically the technique consists of first determining the analogue slope or direction the trajectory should travel in, which as mentioned, is carried out by the LSNA and the scheduler. This slope is the incremental change in y for each unit incremental change in x. For example, a slope of 3.2 means that for each unit step made in the x direction, 3.2 unit steps have to be made in the y direction. However, one cannot make 3.2 steps in a digital picture. Therefore, for each step taken in the x direction, an integer number of steps which does not exceed the value of the slope is taken in the y direction and the remaining fraction is tallied. In the example just stated, one would make one step in the x direction, and three steps in the y direction, tallying the remaining distance to be travelled in the y direction - (.2). Each time this tally exceeds an integer, the latter is added to the number of y steps to be taken. Three examples of this technique are presented in Figure 79.

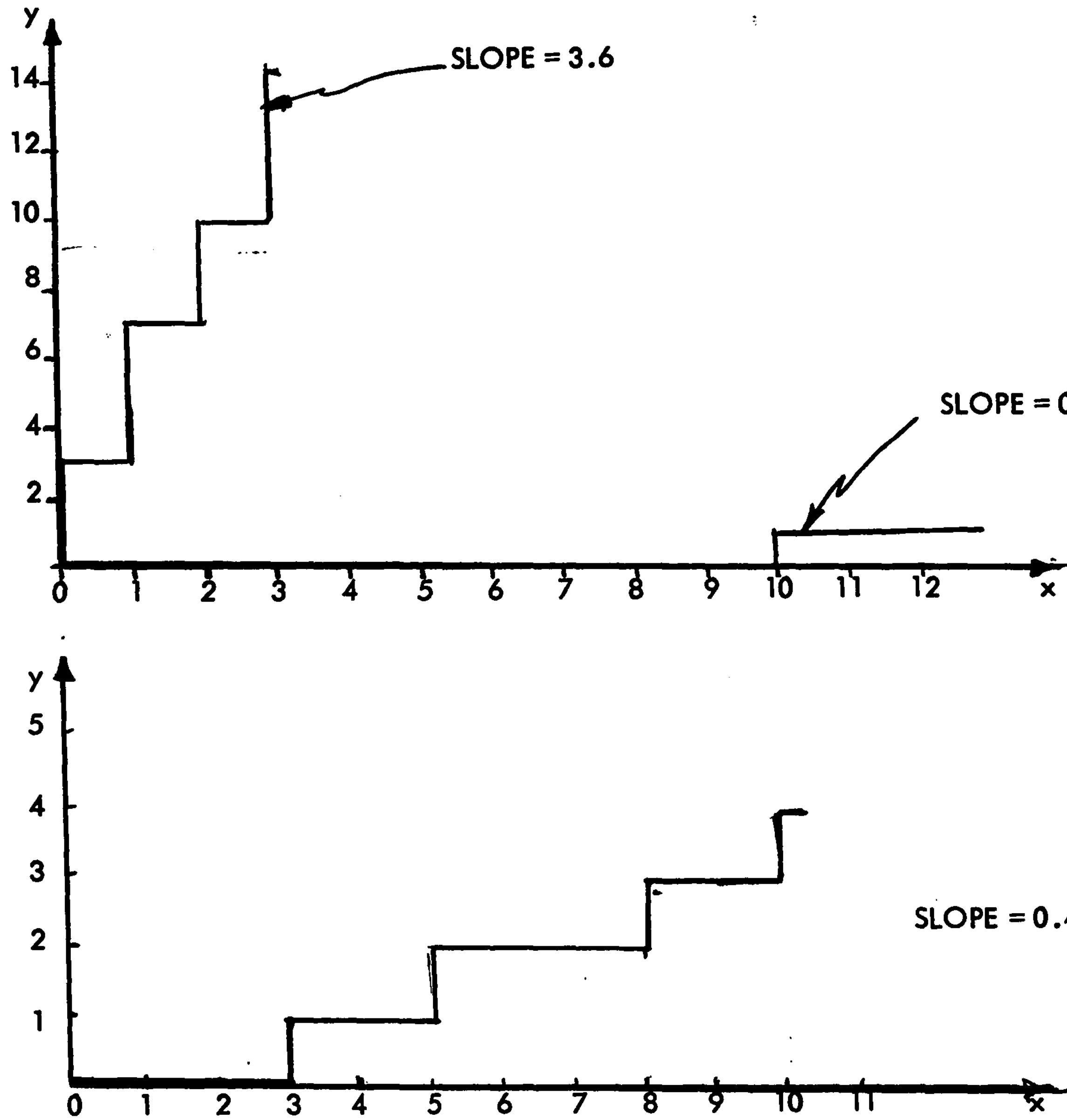


Figure 79 Digital Approximations to Analogue Slopes

After the TA has generated a trajectory segment, the Scheduler takes over and gives control to either the Sensed Travel Mode or the Pass Travel Mode in order to generate the next segment of the next trajectory. Finally, when all of the trajectories have been extended by one segment, the Scheduler passes control to the Intersection Analysis.

6.9 Intersection Analysis (IA)

The purpose of the IA is to tally all points where at least two trajectories cross. This analysis is complete when either a total of five intersections is found, or at least two trajectories have travelled completely through the fingerprint.

The number of intersections sought is chosen as five for two reasons. First, if it is assumed that the trajectories which initially span the field arrive at a common intersection point, then the trajectories must travel closer together. Second, if it is further assumed that adjacent trajectories will intersect each other before they intersect more distant trajectories, then only five intersections (where each trajectory intersects its nearest neighbor) need be considered. Further, only the first intersection between two given trajectories is considered. This restriction is to ensure that intersections amongst the trajectories, rather than five intersections of two trajectories with each other are used in the final analysis. Hence, by choosing five intersections in the above manner, one can stop the analysis when one is reasonably sure of finding a reference point.

The second type of termination-two trajectories travelling completely through the fingerprint-is undesirable for two reasons. First, it may indicate that at least two trajectories have not intersected any other trajectories, and therefore no common intersection point can be reasonably defined. Second, even if these two trajectories do interest other trajectories, five intersections have not been found and again no common intersection can be defined. Note that the trajectories are generated a segment at a time so that they all proceed more or less at the same rate through the fingerprint. Therefore, if two trajectories pass completely through the fingerprint, one can be reasonably sure that the other trajectories will also pass through the fingerprint within a few more segments. Hence, since no common intersection can be defined, the analysis is terminated for this initial search field.

If the first type of termination occurs, the reference point is defined as the average of all the intersection points so long as any given intersection point is within a certain maximum distance of the average point. This distance is chosen as the average distance between two ridges in a fingerprint. In practice, this number is about 1 millimeter, but has to be individually determined for each digital fingerprint.

If the second type of termination occurs, then the initial search field is reduced and the Master Processor re-initializes the whole analysis starting with the Trajectory Initialization. If several analyses with reduced field have failed and the final search field used spans less than one-fifth of the whole print, the fingerprint is considered unsolvable and further searches are aborted.

The heart of the IA is the crossing algorithm, which is explained below.

6.9.1 Crossing Algorithm

There are basically two methods to determine whether any trajectory segment has crossed any other trajectory segment. The first method is the rather unenlightened brute force technique of analysing each segment of a trajectory with respect to all other segments of all other trajectories. It is important to realize that if the number of segments is large, then the number of analyses required by the brute force technique could be prohibitive. For example, if one has six trajectories, each consisting of twenty segments, then six thousand intersection analyses would have to be made. As the number of segments increases, the number of analyses that would have to be made increases nonlinearly.

If possible, one would only like to make those analyses which would guarantee an intersection, or failing this, analyse those segments which show the most promise of intersecting. Now, if one wants to guarantee that an intersection will occur, then one has to use a brute force technique as mentioned. But, from a few basic consideration, one can deduce another method which will find those segments that show the most promise of intersecting. Such a method - developed by the author - is called the Ruler method and is explained below.

6.9.2 The Ruler Method

First, consider a euclidean space, an orthonormal coordinate system and two line (trajectory) segments A and B as shown in Figure 80. Here u, v, and w, z are the

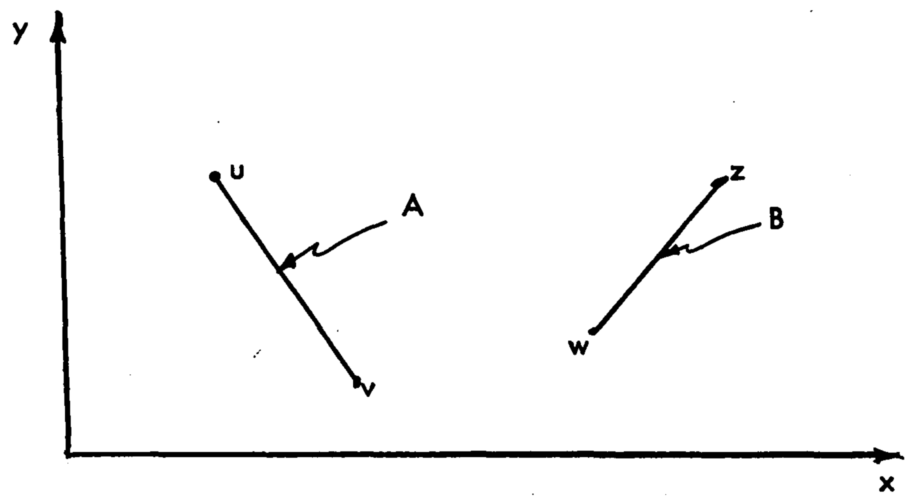


Figure 80 Coordinate System

defining end points of the line segments A and B respectively, where

$$x_u < x_v$$

$$x_w < x_z$$

$$y_u > y_v$$

and $$y_z > y_w.$$

Next, one can define the x and y regions of influence of the line segments A and B as follows (Figure 81).

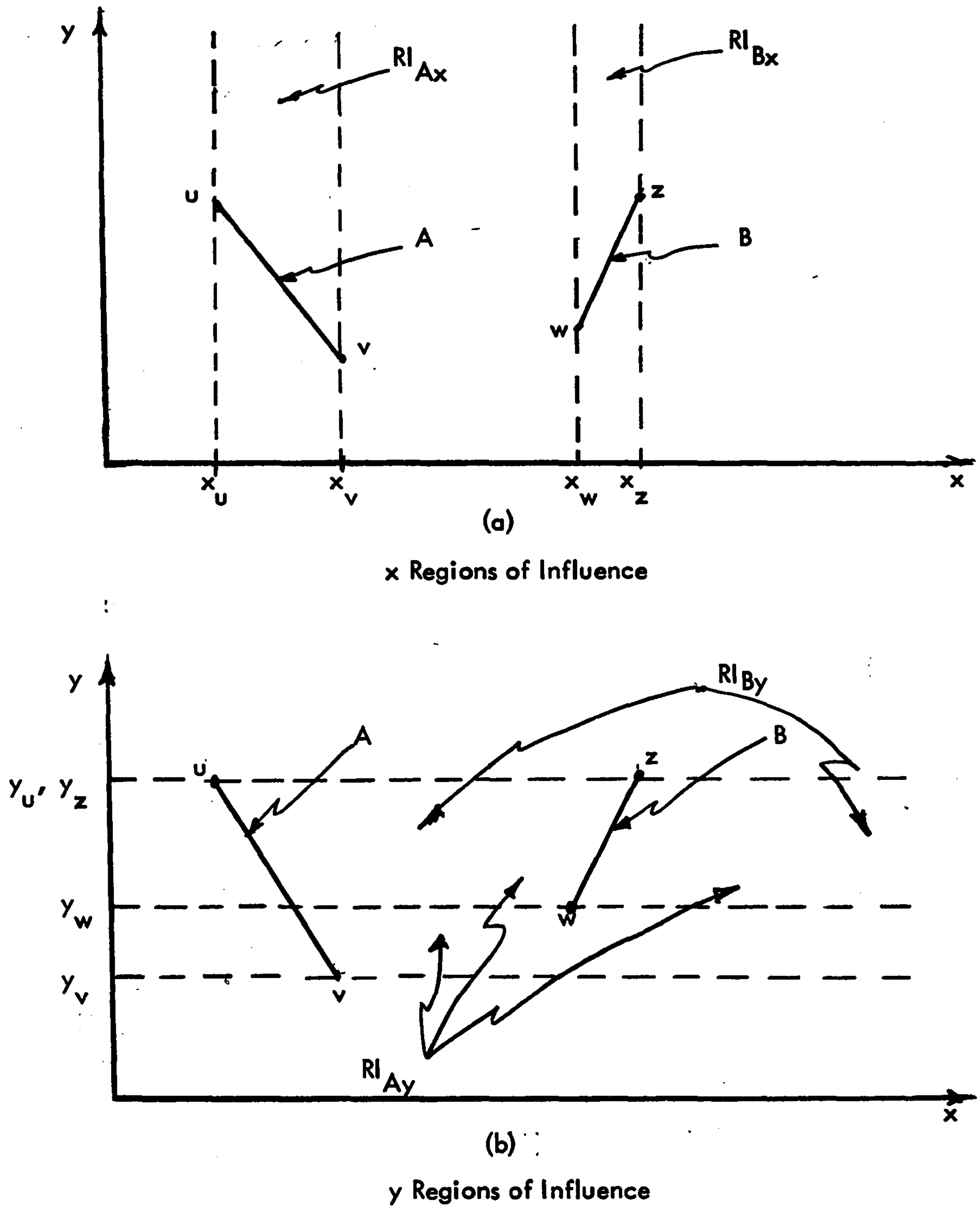


Figure 81 Regions of Influence

$RI_{Ax} \triangleq$ x region of influence of line segment A

$RI_{Bx} \triangleq$ x region of influence of line segment B

$RI_{Ay} \triangleq$ y region of influence of line segment A

$RI_{By} \triangleq$ y region of influence of line segment B

and

$$RI_{Ax} = x \ni x_u < x < x_v \forall y$$

$$RI_{Bx} = x \ni x_w < x < x_z \forall y$$

$$RI_{Ay} = y \ni y_u > y > y_v \forall x$$

$$RI_{By} = y \ni y_w < y < y_z \forall x \ .$$

Now, the region of influence of line segments A and B are defined as

$$RI_A = RI_{Ax} \cap RI_{Ay}$$

and

$$RI_B = RI_{Bx} \cap RI_{By}$$

respectively. (See Figure 82.)

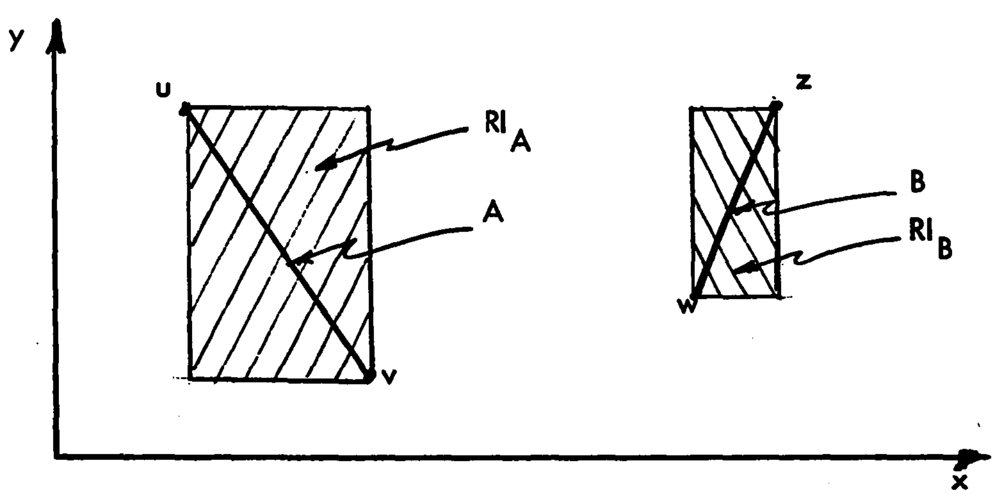


Figure 82 Regions of Influence of Line Segments A and B

Now, since $A \supset RI_A$ and $B \supset RI_B$, the condition for a possible intersection between line segments A and B is:

$$RI_A \cap RI_B \neq \varphi \qquad \text{Relation 1}$$

φ = null set.

This is equivalent to saying that there may be an intersection if and only if

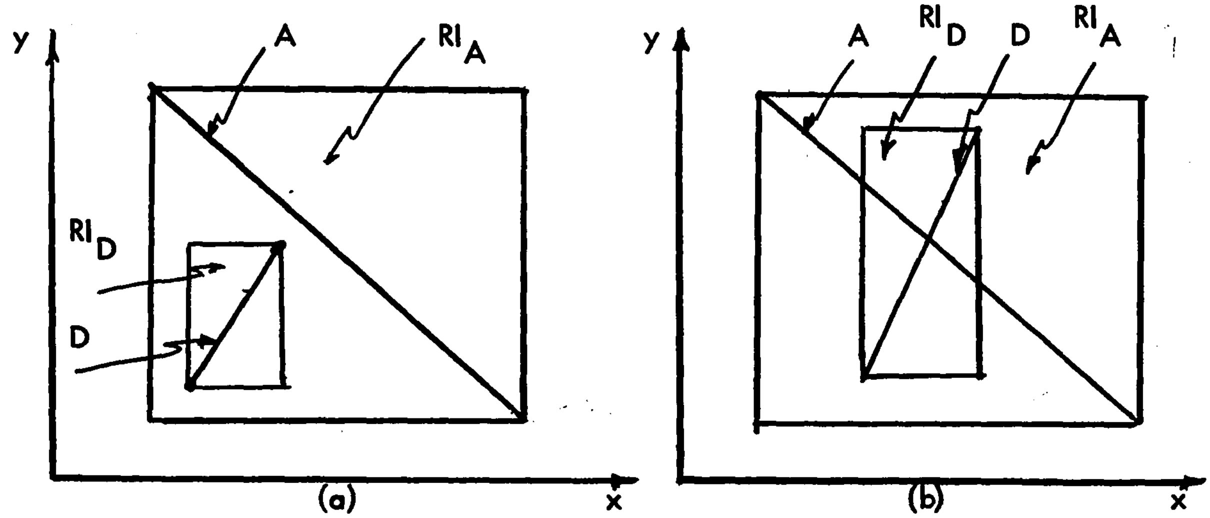
$$RI_{Ax} \cap RI_{Bx} \neq \varphi \qquad \text{Relation 2}$$

and

$$RI_{Ay} \cap RI_{By} \neq \varphi . \qquad \text{Relation 3}$$

These two relations are the core of the crossing algorithm and the key to the Ruler method.

One can see that relation 1 does not guarantee an intersection, but merely states that there is a high probability of an intersection existing (see figure 83). By using



$RI_A \cap RI_D \neq \varphi$
No Intersection between A and D

$RI_A \cap RI_D \neq \varphi$
Intersection between A and D

<u>Figure 83</u>

relations 2 and 3, one can determine which line segments have the greatest possibility of intersecting and then fully analyse those line segments. However, one has to be wary that when one uses relations 2 and 3, the time needed to make these tests does not exceed the time it would have taken to analyse all the segments by a brute force technique.

The author used relation 3 in order to set up a simple ruler technique which can be described as follows. Consider that one has six trajectories that have been partially generated. (See Figure 89.). A line arbitrarily called ruler A is set up in the fingerprint.

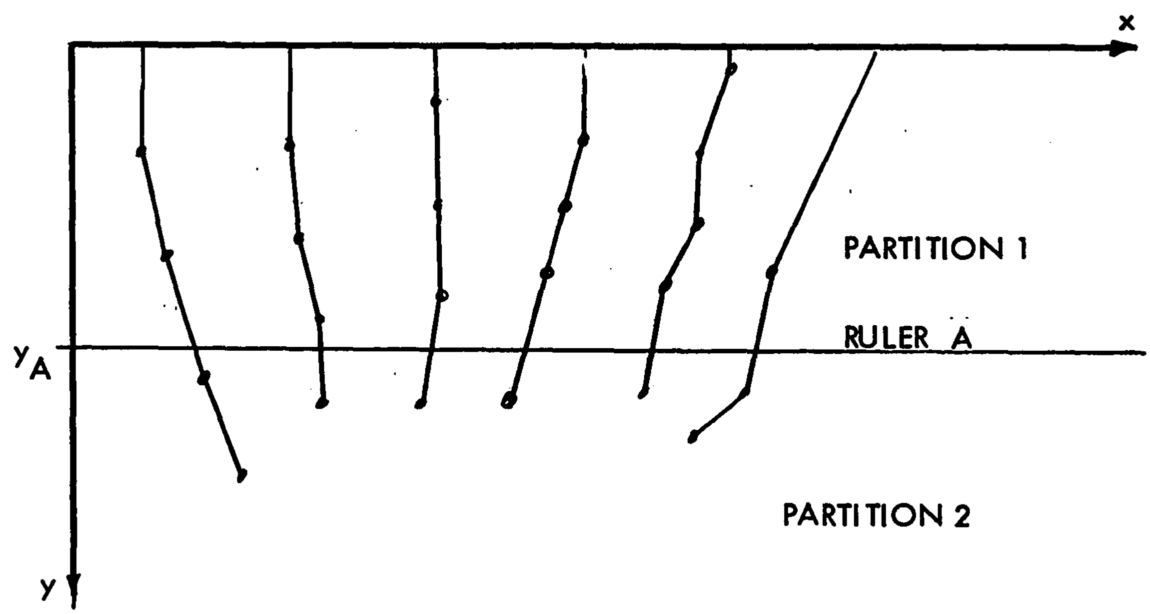


Figure 84 Schematic Representation of Relation 3

parallel to the x-axis. Now, by relation 3, any trajectory segment lying below ruler A ($y < y_A$) in Partition 1 cannot intersect any trajectory segment lying above ruler A ($y > y_A$) in Partition 2. Therefore, if the trajectory segments can be partitioned by using a ruler so that only those segments lying in one partition are examined, then the number of intersection analyses needed to determine which segments intersect, is reduced.

Appendix D explains how the ruler was generated for use in the digital method for finding a reference point in a fingerprint so that the partition to be examined, contained only the last few segments of each trajectory thus reducing the number of crossing analyses needed. One can make variations on the simple ruler method by introducing rulers for relation 2, , and multiple rulers within a given partition, but the author found these too time consuming to be considered for further use.

When any given Intersection Analysis is complete and neither of the termination requirements have been met, the Master Processor directs control to the Supervisor Program of the Slope Analysis so that more segments may be generated. Due to the fact that the listing of this program is thirty-two pages long, it is not included in this thesis. However copies of the program are available from the author.

The next chapter presents and discusses the results obtained by using these algorithms on fingerprints.

CHAPTER VII

RESULTS AND CONCLUSIONS

7.1 Introduction

The digital method explained in the last chapter was applied to a test group of 150 fingerprints. (See plates 1 - 13.) These prints are divided into three groups so as to make the discussion of the results easier and more understandable. Where applicable, the reference points generated in each group are presented as dots located in the fingerprints of the respective groups. The plates are presented in Appendix F.

7.2 Group 1 Fingerprints

This group (plates 1,2) contains all the fingerprints for which the digital method generated and recognized a reference point. The distinguishing feature of the Group 1 fingerprints is that the Intersection Analysis recognized that a central point had been generated.

Note that no one type (Henry classification) of fingerprint predominates the Group 1 fingerprints.

7.3 Group 2 Fingerprints

This group contains other fingerprints (plates 3 - 11) for which a reference point was generated. The characteristic feature of this group is that the IA did not recognize that a reference point was generated. However, all the trajectories of the Group 2 fingerprints did have a common intersection point which was visually extracted from the analysis. Some of the fingerprints of this group have more than one reference point. This non uniqueness of the reference point will be discussed in Section 7.5.

The reason why the reference points for this group remained unrecognized is that certain peculiarities in the trajectories foiled the Intersection Analysis. It was initially assumed that in travelling through the fingerprint, the distance between all of the trajectories would decrease until finally a common intersection occured. (Figure 85.)

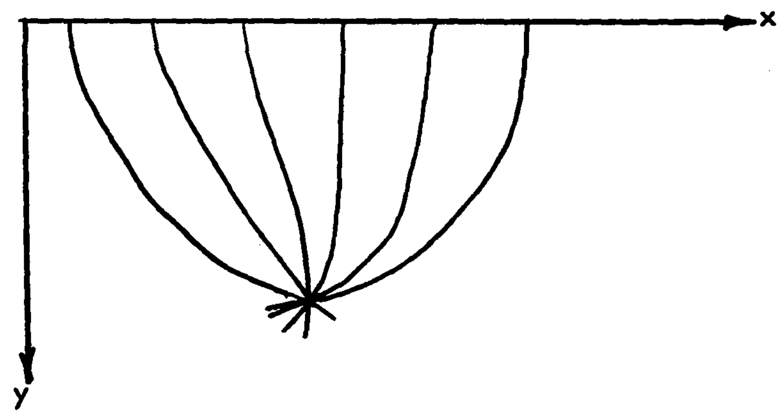


Figure 85 Assumed Trajectory Travel

However the analysis indicated that this was not the case. For all of the fingerprints in the second group, trajectory crossings which were distant from the common intersection point were generated. For the purposes of discussion these distant crossings will be called false crossings. The false crossings occurred mainly because of the combination of large quantities of ridge noise and a trajectory's lack of inertia. The inertia of a trajectory depends upon how many segments have been generated, and the delay factor which is used by the Scheduler Program (page 109) to determine the next direction of travel. The majority of false crossings occurred within the first four segments of a trajectory. This is due to the combined fact that either the delay factor (n = 3) had not yet entered the Scheduler Program's direction considerations, in which case the direction was solely determined by the ridges which were very noisy, or that the delay factor was just initiated and as yet did not yet have much effect in determining the trajectory's direction. The remainder of the false crossings were solely due to ridge noise. Two false crossings (A, B), a common crossing (c), and typical trajectories for Group 2 fingerprints are presented in in Figure 86.

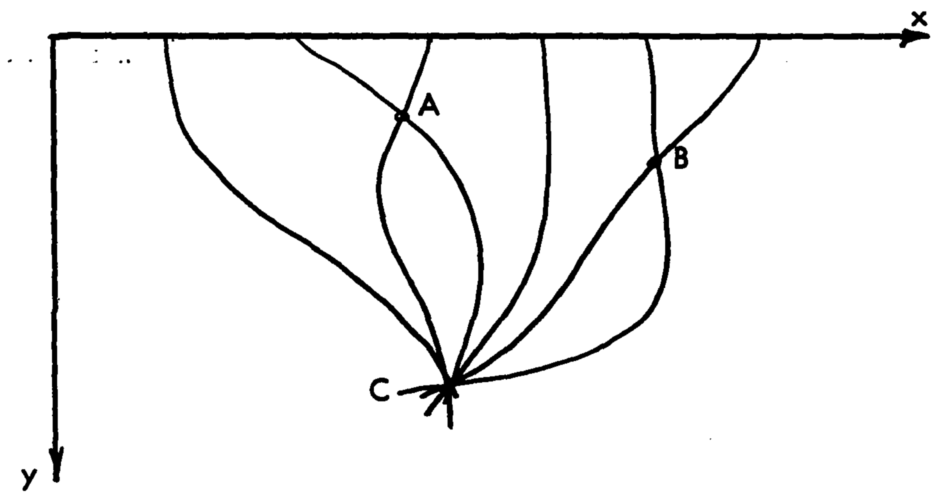


Figure 86 Trajectories Generating False Crossings

As was mentioned previously (page 113), the Intersection Analysis takes the average of the first five crossings as a possible reference point. Then, the distance between each crossing and the possible reference point is calculated. If this distance is greater than a certain maximum allowable distance (see page 113), then the reference point is discarded and another analysis is automatically made. In all the analyses of the Group 2 fingerprints, one or more false crossings occurred. Due to the facts that an analysis was not terminated until either five crossings were made or two trajectories travelled completely through the fingerprint, and that only the first intersection between any two trajectories was recorded, the trajectories did generate a reference point. However, because of the maximum distance criterion just mentioned, these reference points were not located by the machine, but instead had to be identified visually.

A second type of false crossing arose solely because of ridge noise and occurred only when the trajectories were very close together. Figure 87 illustrates this type of false crossing (1,2,3,4) generated by trajectory f because of the large amount of noise in the ridge region near f.

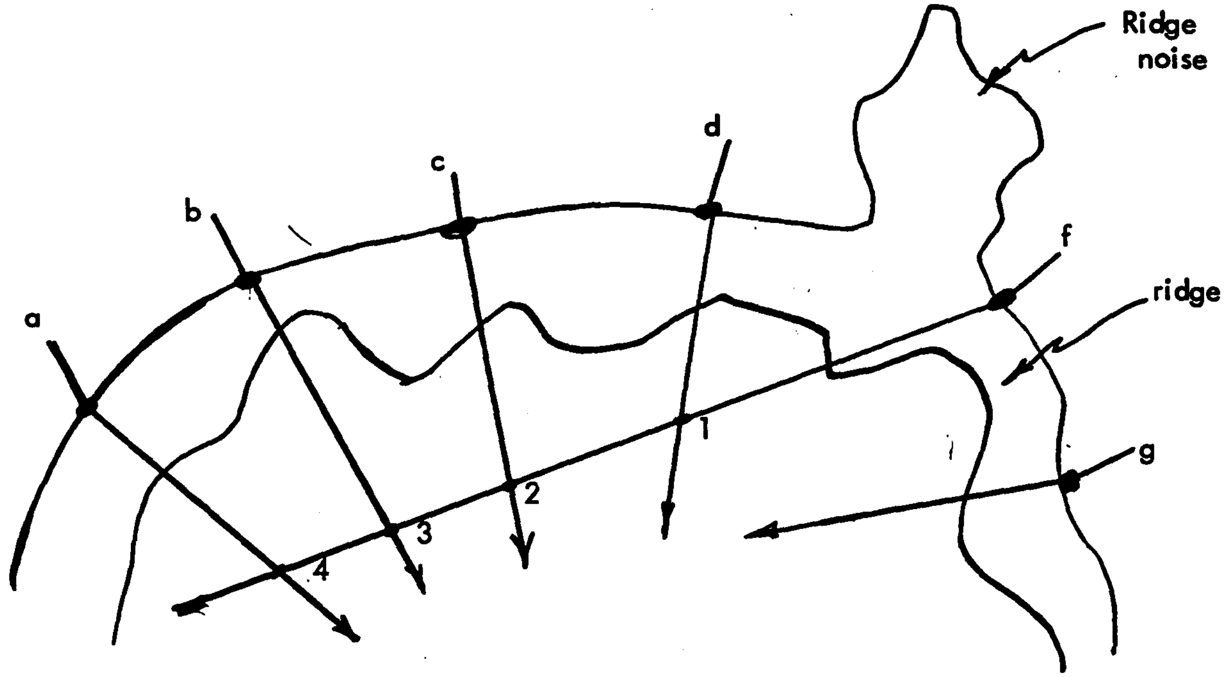


Figure 87 False Crossings due to Ridge Noise

Since all of the trajectories are very close, one can be reasonably sure that a common intersection point exists in a small region about this type of false crossing (1,2,3,4). Here, the only problem is to determine which trajectory is causing all the false crossings and either eliminate it from further analysis, or force it to travel in the same general direction as the other trajectories.

One way to eliminate the effects of the first type of false crossing that was mentioned would be to allow all of the trajectories to travel completely through the fingerprint and log every intersection that occurs. Next, one would calculate a weighted average of the intersection points and then eliminate from further calculations those points which lie farthest from the weighted average. Using the remaining points, another weighted average could be calculated. This type of elimination and calculation would continue until either all the remaining intersections lie within the maximum allowable distance needed to define a reference point or no intersection remained within this distance. Here, however one would have to consider how to weight each intersection and what distance criterion should be used for the elimination of an intersecting point.

Another technique that could be helpful in eliminating the first type of false crossings involves examining the intersection points that form clusters. Here one could calculate the reference point from the most heavily populated cluster. However one would have to define some cluster threshold values in order to determine if a given intersection is a member of one cluster or another.

After considering these problems and some of the ways they could be handled, the author found it impractical to change the digital method for three reasons. First, in all of the fingerprints a reference point can be located by visual examination of the results. Since the major emphasis in this project was to generate a reference point, it is of secondary importance that a machine be able to recognize such a point. Second, in order to be sure that any algorithm would work on all of the Group 2 fingerprints, it would be necessary to test each algorithm on the whole group. In view of the computer time (see Appendix E) taken for the analysis of all the fingerprints, the continued testing was found to be impractical in terms of the time and scope of this project. Third, after analysing the results, it was concluded that a line rather than a unique point was generated. Therefore, there is no point in attempting to perfect the digital method with respect to recognizing reference points.

7.4 Group 3 Fingerprints

The fingerprints in Group 3 (plates 12, 13) are non-solvable by the digital method. This is due to the fact that these prints are either very heavily damaged or excessively noise laden. Here again, no one type of fingerprint (Henry system) predominates this group. Typical analyses for all groups are presented in Appendix E.

7.5 Uniqueness and Repeatability

It has been shown that a reference point can be generated for a majority of the fingerprints examined. However two important questions remain to be answered. The first is, 'Is the reference point unique?' and the second is, 'Is the reference point repeatable?'. The author found that the answer to the second question depended upon the answer to the first. That is, if a reference point is unique, then it will be repeatable. However, that a reference point is repeatable does not imply that it is unique.

In order to answer the first question, one must consider the various types of uniqueness pertinent to the problem. The types that are discussed are: uniqueness under rotation; uniqueness under field reduction, which includes uniqueness under random initialization of the trajectories; and uniqueness under multiple impressions, which is a measure of the absolute repeatability of the reference point.

7.5.1 Rotational Uniqueness

The problem of rotational uniqueness was first considered in the discussion of the Rabinow Electronics method (page 45). It was demonstrated that a reference point is not unique under large rotations of the print. However it was found that if a reference point could be defined, then the same reference point was found if the analysis was carried out for different but small rotations of the fingerprint. The definition of a small or large rotation depends entirely on the fingerprint being examined and as such has no typical value. However the fact that a reference point is repeatable under small rotations does not belie the fact that this reference point is not unique. The uniqueness (small scale rotations) and non uniqueness (large scale rotations) of the reference point can be understood in terms of the gradient technique of hill climbing used to generate the trajectories. For example, consider a trajectory analysis of Figure 88. Here, the trajectories would remain

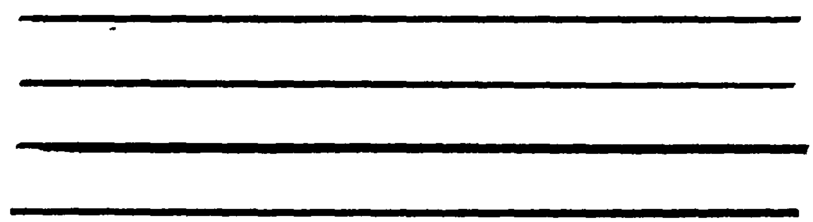


Figure 88 Ridges of Zero Curvature

parallel to one another and travel through these ridges without intersecting each other. In order to generate a reference point and hence have the trajectories intersect, the ridges must have some finite radius of curvature (Figure 89) which acts as a focussing agent for the trajectories.

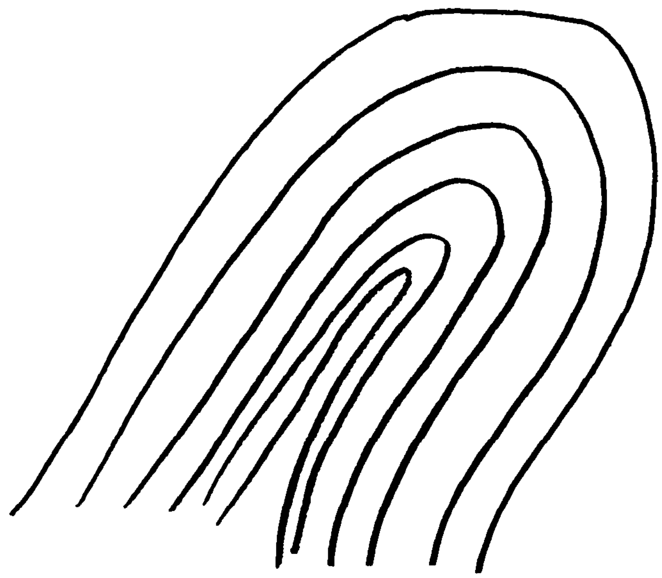


Figure 89 Ridges of Non-Zero Curvature

The situation encountered by the digital method in examining Figure 88 is analogous to a problem where the gradient technique is applied to a constantly increasing or decreasing function. Now, it can be seen that certain sections of Figure 89 appear as parallel lines with almost 0 curvature. (See Figure 89.) These sections are highlighted in Figure 90. It was found that any trajectories that were initialized along such sections

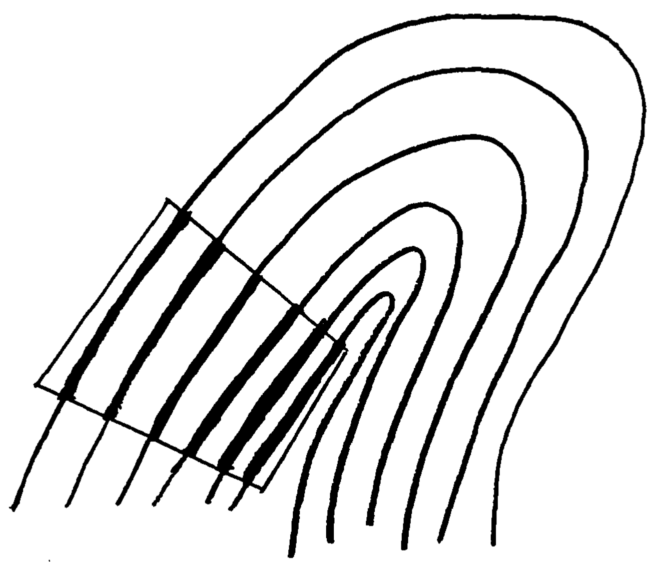


Figure 90 Approximately Parallel Ridges with Zero Curvature Extracted from Figure 89 (highlighted)

did not necessarily have a common intersection with each other, but might have had a common intersection (within the maximum allowable error limits) with the trajectories that were initialized on the more curved portion of the fingerprint. It was also found that if all the trajectories were initialized in the region of maximum curvature of a ridge, then a common intersection point was found. Further, if all trajectories were initialized in a region of minimum curvature, then either no reference point was found or a point was generated that was different from the one that was found for 'maximum curvature' trajectories. Therefore one can define the maximum rotation of a fingerprint for a repeatable reference point to be that rotation which ensures that no trajectory 'sees' a set of ridges such as appear in Figure 88. For purposes of the following discussion, the common intersection point resulting from initializing all trajectories in a region of maximum curvature of a ridge will be called the 'optimal' reference point or peak.

If one considers the optimal reference point as the peak of a mountain and the ridges of a fingerprint as contour elevation lines, then the failure of the digital method to generate a unique reference point can be understood in terms of the failures of a gradient technique of hill climbing. Figure 91 shows the top and side elevation aspects of a fingerprint viewed as a mountain. A gradient technique can fail for three reasons. First, if the peak located is actually part of a plateau, then it is not unique. Second, if a sharp ridge is encountered, the gradient method will result in trajectories which oscillate about the ridge. Third, if two definite peaks are apparent, then the gradient technique will locate the closest peak. The rotational non uniqueness (large rotations) is related to the first and third types of failure of the gradient technique. Consider that any two points on a plateau are at the same elevation. If one is looking for the maximum elevation of a butte, then any point on the plateau will define the maximum elevation.

Hence even though the elevation may be unique, the point that defines the elevation is not unique.

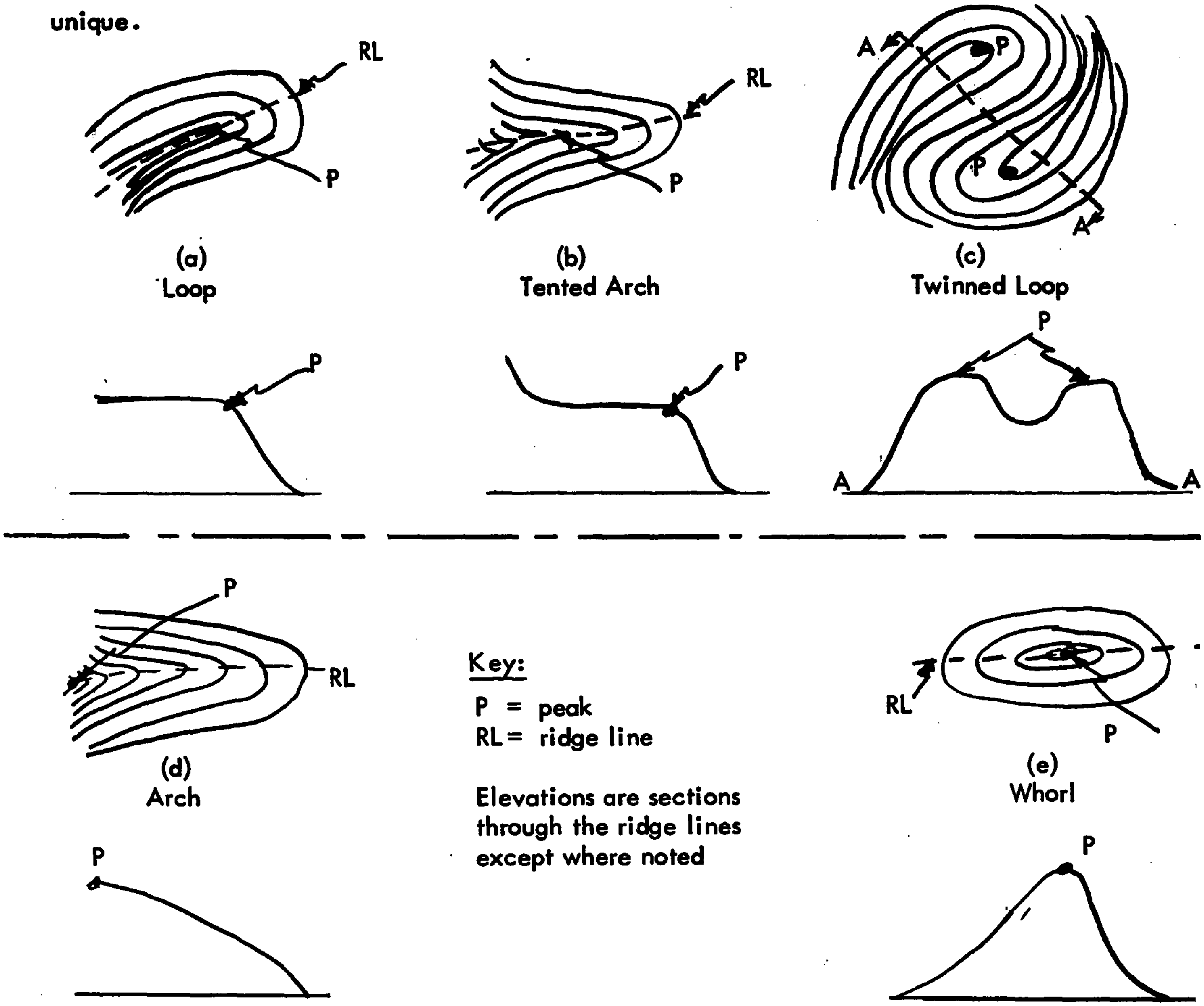


Figure 91 Fingerprints Viewed as Mountains

If for certain types of fingerprints with pronounced plateaus (Figure 91 a,b,c), the print is rotated so as to present some parallel ridges of approximately zero curvature to a trajectory, then these trajectories will travel over the plateau. In doing so, these trajectories will intersect any other trajectories that are travelling along the ridge line.

This can be seen in Figure 92. Hence any fingerprint that has a plateau (Figure 91 a,b,c) cannot have a unique reference point in terms of the digital method.

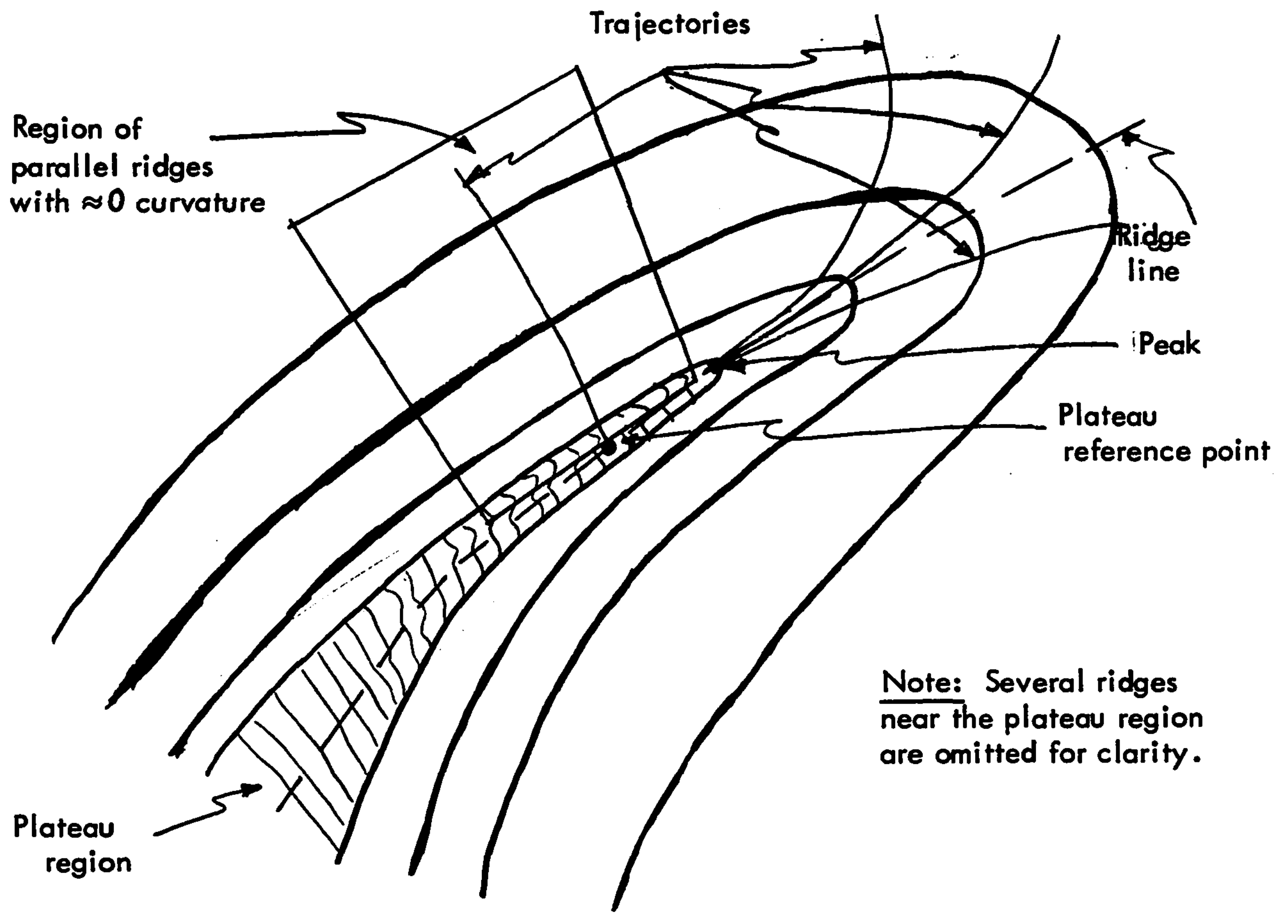


Figure 92 Generating a Plateau Reference Point

7.5.2 Field Reduction and Uniqueness

It was mentioned (page 113) that if the Intersection Analysis could not recognize that the digital method had generated a reference point, then the field of search was reduced and another analysis was automatically made. It was found that, in general, each reduced field analysis of a given fingerprint in the second group generated a reference point and these reference points were different from one another. The reason for this can be related to the second mode of failure of a gradient technique as mentioned previously (page 128).

If a gradient technique encounters a ridge line, it will tend to oscillate about that ridge line. Further, the closer one starts to a ridge line, the sooner the gradient search will oscillate. In terms of the trajectory analysis, it was observed that each trajectory tended to oscillate slightly about an assumed ridge line and that these oscillations caused intersections between the trajectories. Also, it was observed that the closer that these trajectories were to the assumed ridge line initially, the sooner this occurred. It turned out that these intersections generated reference points upon the assumed ridge line. Since each field reduction generated a different reference point, a reference point is not unique under field reduction.

Upon further investigation it was observed that a line of globally maximum curvature (GLOM) - that line which connects the points of maximum curvature of all the ridges of a fingerprint - could be generated by the digital method. Also, even though the trajectories intersected one another as they oscillated about the GLOM, they all tended to follow the ridge line and hence define the GLOM as indicated in Figure 23. One final test was made whereby the trajectories were given random starting points. It was observed that if a reference point was defined, it lay on the GLOM of that fingerprint, otherwise no reference point was found.

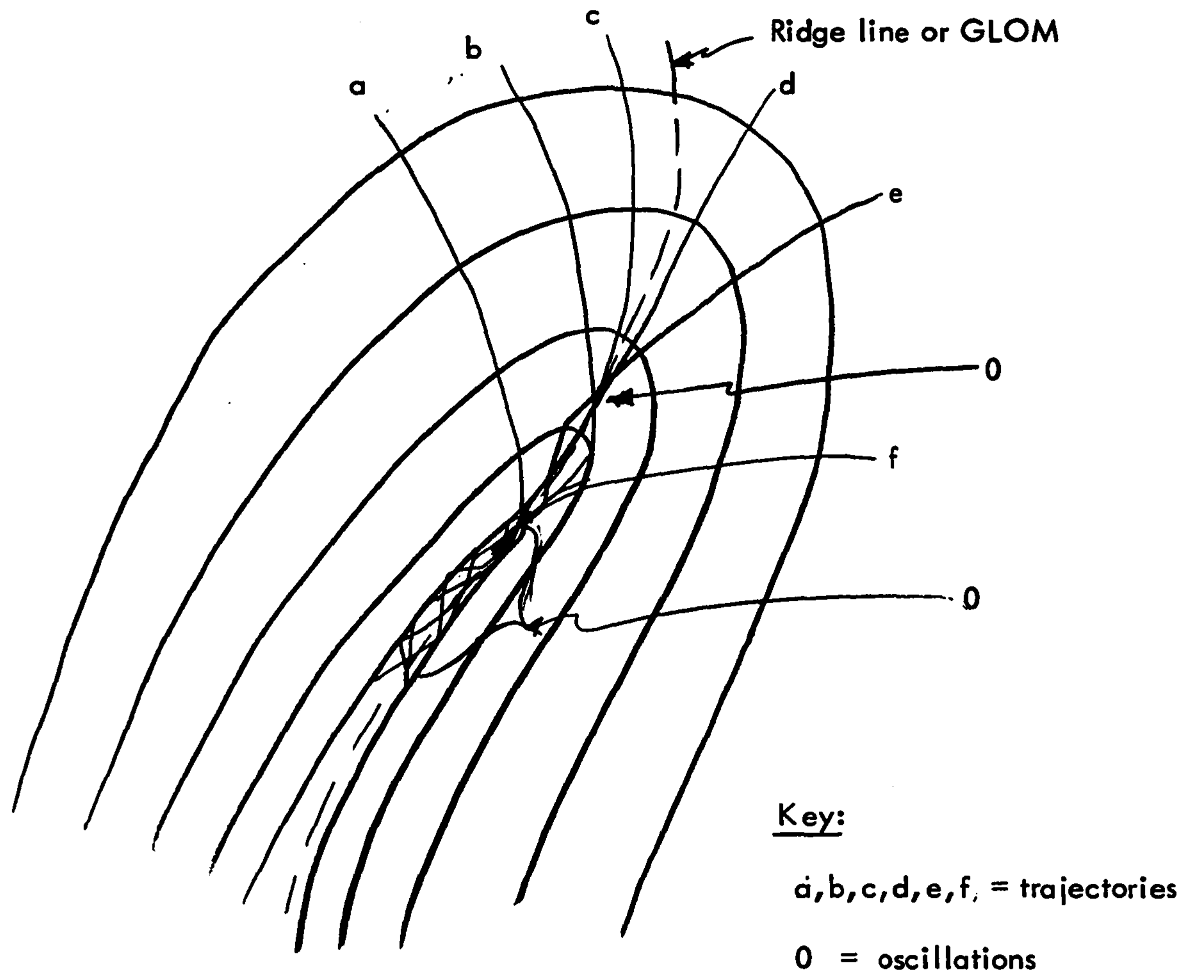


Figure 93 Trajectaries Following the Ridge Line (GLOM)

It is interesting to note that the GLOM is similar to the line that connects the 'top nodes' as defined by Hankley and Tou[12]. However, the 'top nodes' are the local points of maximum ridge curvature whereas the GLOM defines the global points of maximum ridge curvature. The GLOM will be discussed further in the conclusions.

7.5.3 Multiple Impressions and Uniqueness

If upon using the same fingerprint and the same analysis (including small rotations), a given reference point can be generated more than once, the reference point is considered to be relatively repeatable. If this same reference point can be generated in a different impression of the finger, then the reference point is considered to be absolutely repeatable. This means that the correct point was found regardless of the smudging, distortion or absence of data which is evident in multiple impressions of the same finger. However, since the reference points generated were not unique within a fingerprint, the author considered that an examination of multiple impressions was not warranted and hence was not made.

7.6 Conclusions

A digital method for generating a reference point in a noisy fingerprint has been presented. It has been demonstrated that a reference point can be generated in a majority of the fingerprints examined. It has also been shown that the reference points so generated are not unique. Hence, the location of the reference points presented in Sections 7.2, 7.3, and 7.4 are meaningless and are just quirks of the fingerprint being examined. Because of this fact, the author feels that further work on this digital method for generating reference points is unnecessary. In addition to the above, the literature on automatic fingerprint analysis was reviewed.

In considering the future of fingerprint analysis - automatic or otherwise - one can consider two broad categories: ten finger systems and single finger systems. In view of the success of the Henry system (ten finger, topological, manual) and the Hankley and Tou system (single finger, topological, automatic), the author feels that only a topological classification system could capably deal with the many distortions that naturally appear in fingerprints.

7.6.1 Ten Finger Systems

It is considered that the time is long overdue for a serious reappraisal of the Henry system. After all, Henry proposed a system based on observations made on a relatively small sample of the total number of extant fingerprints. This author feels that the large sample of ten finger files existing today (177,000,000 files for the FBI alone) would provide ample grist for any stouthearted statistician's mill. Even a taxonomist would have a field day with the chaotic classifications that presently exist.

It would be a large undertaking to regroup the extant ten finger files according to a different topological code, but several advantages to this regrouping are evident. If a set of primary classifications could be defined that contains a more even distribution of files, then the search and identify time could be dramatically reduced. As it stands now, some primaries are so heavily populated that it is a farce to call such a primary an initial classification. This type of classification is equivalent to a classification which separates the human population of the world into 'male' and 'female' and 'neuter'. The regrouping of primaries would be efficient in terms of employee time, since essentially only new header cards for the primary classifications would have to be supplied. That is, all the secondary classifications would remain the same, yet the relative ease with which one could locate a file by its primary classification would be increased. It must be remembered that the above is only a prospectus and may be more laborious than envisioned, but the author feels that this approach should not be neglected.

It is interesting to note that certain similar genetic characteristics result in similar fingerprint patterns[27] (gross descriptors). Therefore one region of a country may have certain primaries (in the Henry system) full of files while other regions may have the same primaries nearly empty. Thus in making a study such as the one proposed, care would have to be taken so that a 'regional' system of primaries (such as the Henry system) is not developed. This means that in the least one would have to work with many state or provincial files, but preferably with national files.

7.6.2 Single Finger Systems

The only thing that detracts from ten finger systems is that it is useful only for identifying the victim, not the murderer. That is, all ten fingers are needed for a classification. Therefore any ten finger system that is used can be considered a victim's system. However what is needed is a murderer's system - one that can identify people from single fingerprints.

The author feels that the classification of single fingerprints is the rightful realm of an automatic (digital computer) method even though a manual (Battley) system does exist. The problem with the manual system is that it is time consuming and requires at least ten times as much effort and storage space as the Henry system. In this light, the author advocates further research into the GLOM as defined by the digital method in conjunction with the topological single fingerprint machine method developed by Hankley and Tou[12]. The reason for this is that at present Hankley and Tou's method works only on selected, partially noise filtered data. Further, by virtue of the way in which the search for the top nodes is made, only points of locally maximum curvature are found. Therefore, depending on which rotational configuration is analysed, different classifications may result. The digital method provides a way to generate the top nodes in extremely noisy data such that the line of globally maximum curvature is extracted (GLOM). The extraction of the GLOM occurs by virtue of the fact that six trajectories are used in conjunction with each other. Essentially each trajectory follows a line of locally maximum curvature until the trajectories find a common intersection. Thereafter the trajectories walk along the GLOM. This can be seen in terms of a gradient technique whereby the trajectories reach a ridge line and then proceed to walk along the ridge line. Further areas for research into the GLOM are indicated. For example, how could one best initialize the trajectories so that they will reach the ridge line quickly? Also, can special types of field reduction be employed so that the trajectories will approach the ridge line rapidly?

In fine, the author considers it of importance to be able to automatically classify and identify fingerprints, and that the use of the digital method in conjunction with Hankley and Tou's method would perhaps be the next most logical step in this endeavour.

APPENDIX A

The following three quotations are presented as indications of both the usefulness of fingerprints for identification purposes, and the other users researchers have for dermatoglyphs or skin carvings in general.

> "I beg the indulgence of the court while I make a few remarks in explanation of some evidence which I am about to introduce, and which I shall presently ask to be allowed to verify under oath in the witness stand. Every human being carries with him from his cradle to his grave certain physical marks which do not change their character, and by which he can always be identified - and that without a shade of doubt or question. These marks are his signature, his physiological authograph, so to speak, and this autograph cannot be counterfeited, nor can he disguise it or hide it away, nor can it become illegible by the wear and mutations of time."
>
> "This signature is not his face - age can change that beyond recognition; it is not his hair, for that can fall out; it is not his height, for duplicates of that exist; it is not his form, for duplicates of that exist also, whereas this signature is each man's very own - there is no duplicate of it among the swarming populations of the globe!..."
>
> "This autograph consists of the delicate lines or carrugations with which Nature marks the insides of the hands and the soles of the feet..."
>
> Mark Twain[35]

"In medical works, haematoma of the ear has long been recognized. This consists in the upper portion of the ear assuming a peculiar shape, either by the formation of a blood tumor, or by the thickening of the upper portion, which is found in the ears of lunatics, generally those who inherit madness; but in Paris lately it has been more closely studied, with the result that in August 1893 tests were given before the Académie des Sciences, proving that madness could be predicted years in advance by a proper study of the ear alone. Now my argument is, that if, as has been proved, accurate prediction can be made by a study of the ear, is there then anything impossible in prediction being far more accurately made by a study of the hand, which has been pronounced to be, both in nerves and mechanism the most wonderful organ in the entire system, and to have the most intimate connection with the brain."

Cheiro[3]

"A point which deserves some comment is that the occurrence of a radial loop on the ring and small fingers has been cited as having particular significance as an indicator of mongolism."

Lu[20]

Mark Twain's quotation eloquently describes the prime use of fingerprints – that of identifying the individual. The second and third quotations, although separated by some seventy years, indicate the direction that the study of dactylography is taking. Cheiro's statement is part of a defense of palm reading as a science. The fact that there are thousands of recorded readings with close to one hundred per cent accuracy backing up this 'science' should lead us to think rather than to laugh. Lu's sentence comes from a modern biomedical paper that describes the research being done to determine the fingerprint types that are indicators of Down's syndrome.

It is fascinating to contemplate that we may be applying mechanical techniques of pattern-grokking to the occult or scientific endeavours mentioned and be able to help prove, disprove, or formulate new theories dealing with dermatoglyphics. If something can indeed be read from the palms and fingerprints by human observers, then the field of automatic pattern-grokking or scene analysis has much more new material to work with in codifying identity descriptors.

APPENDIX B

This appendix contains examples of ridge noise that could be mistaken as minutiae

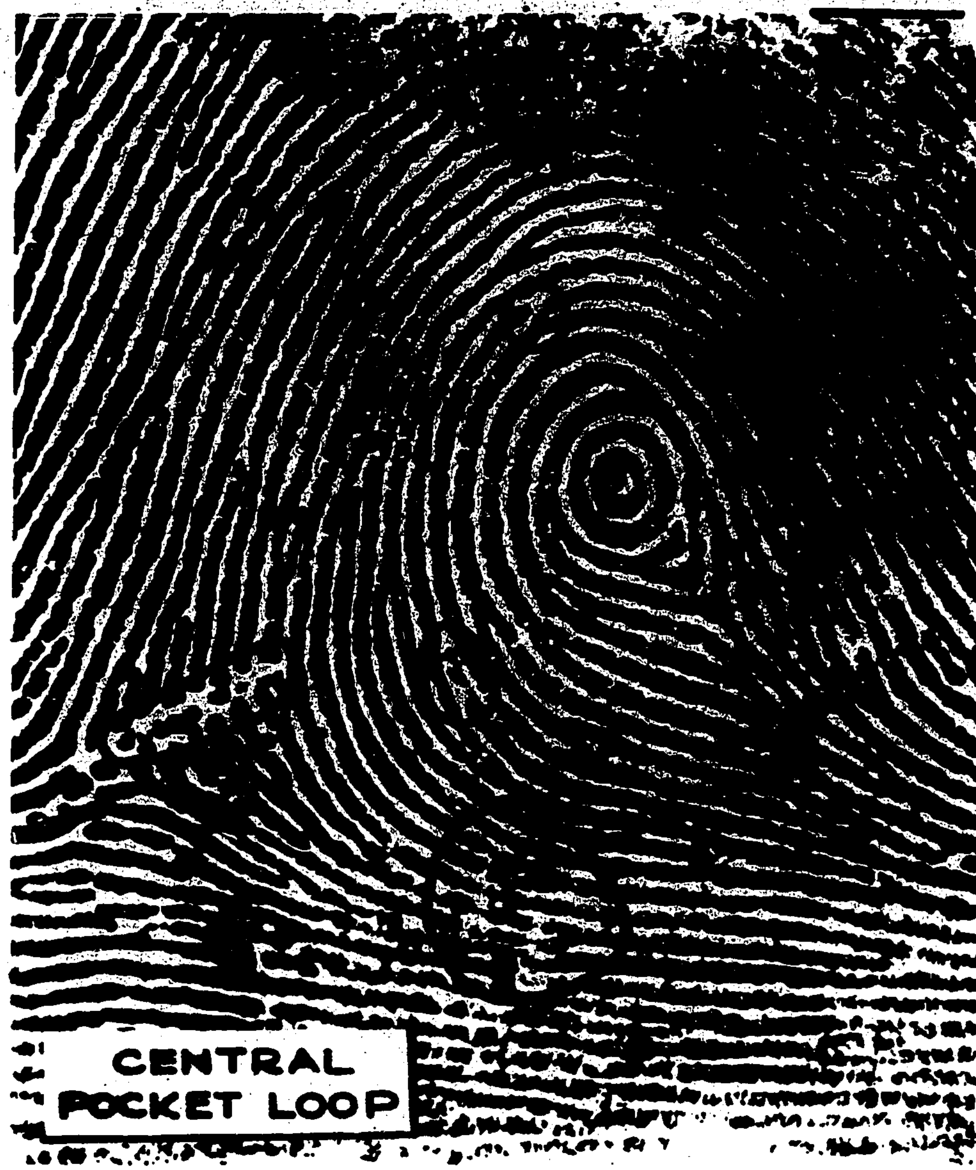


Figure B-1

Figure B-1

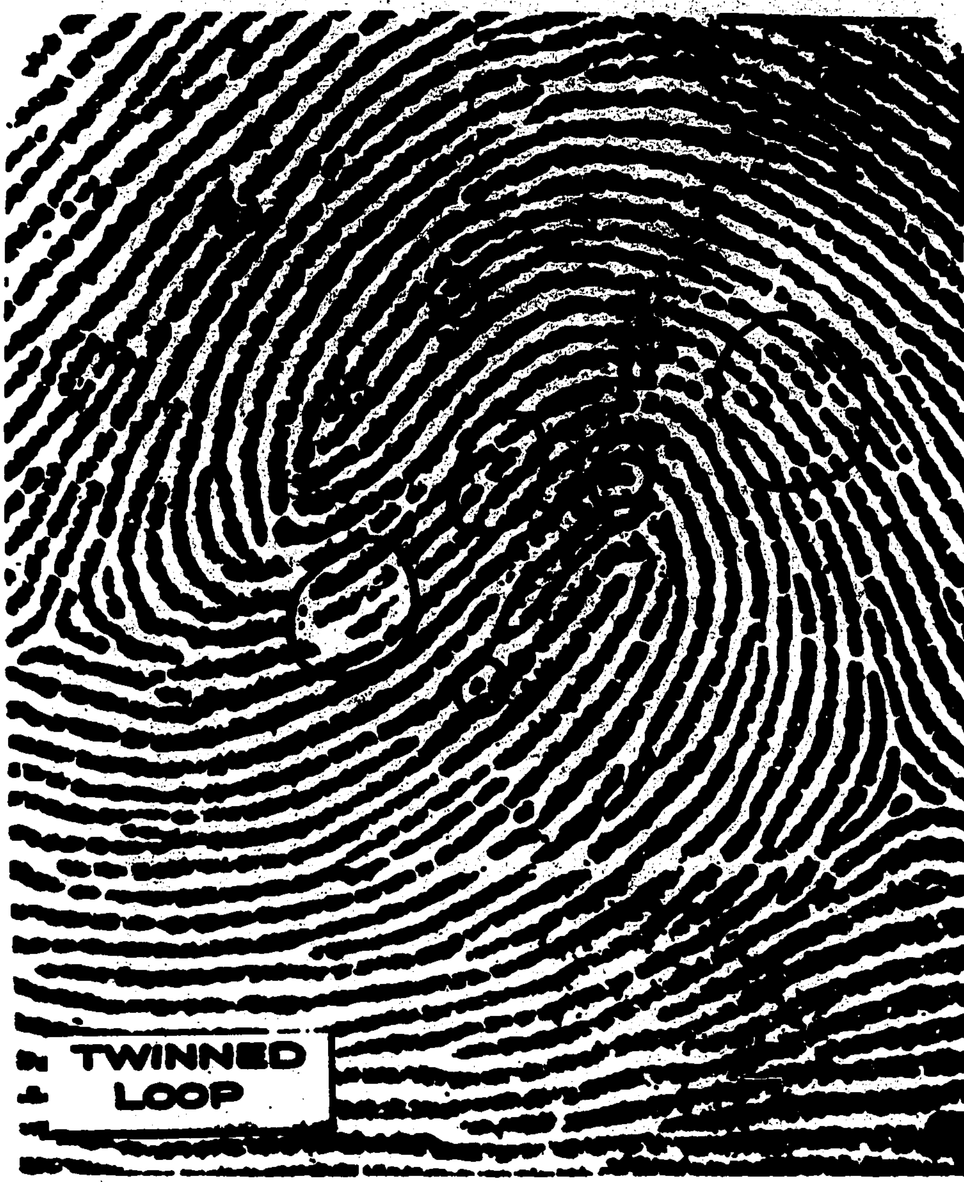


Figure B-2

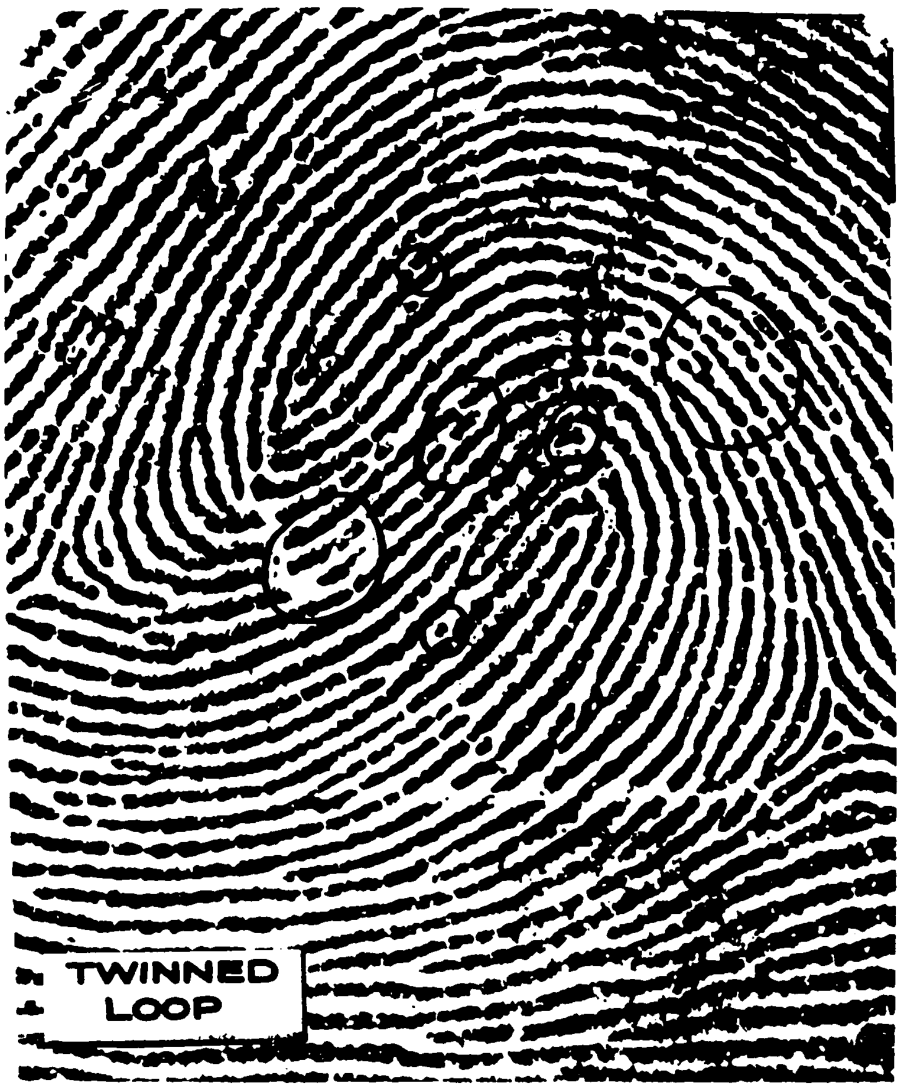


Figure B-2

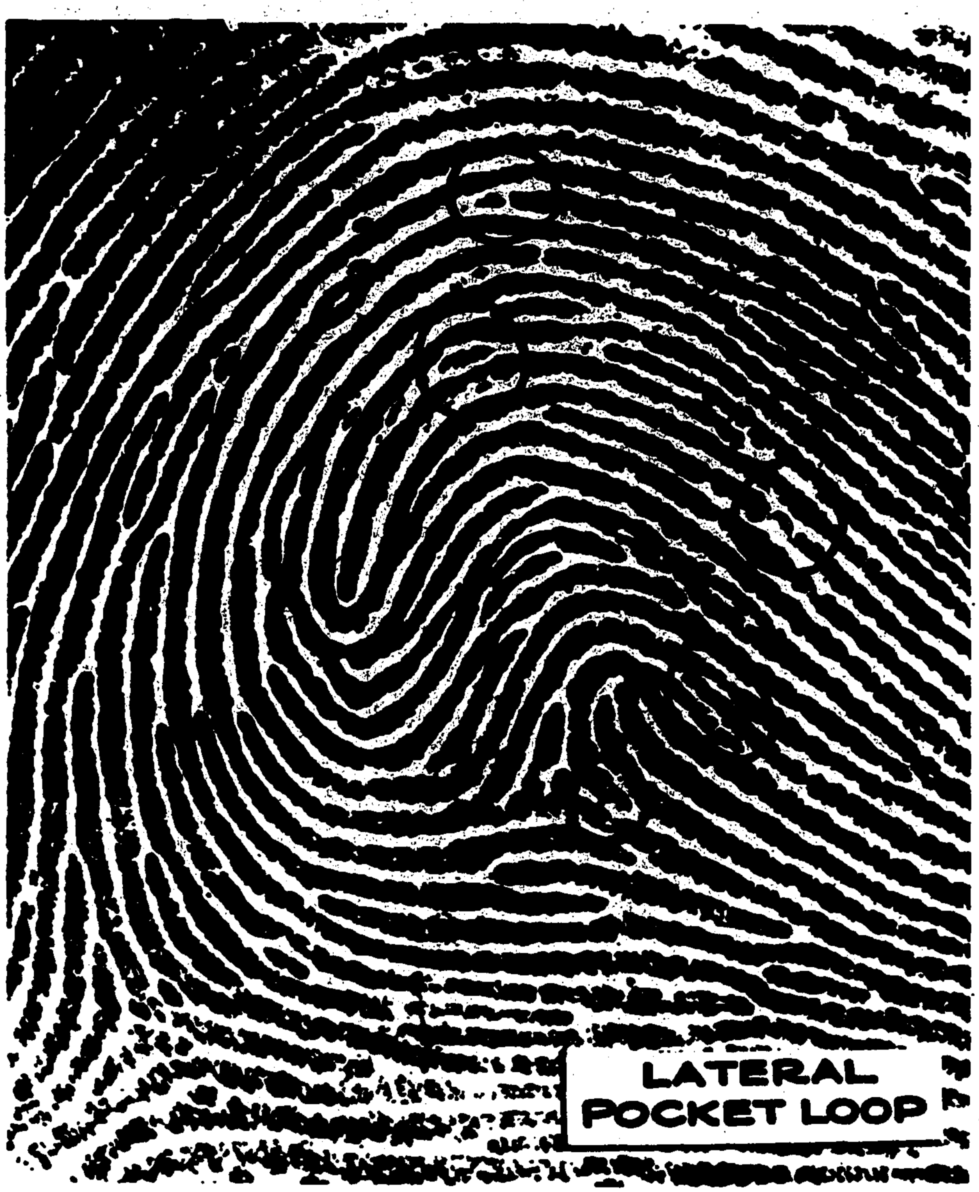


Figure B-3

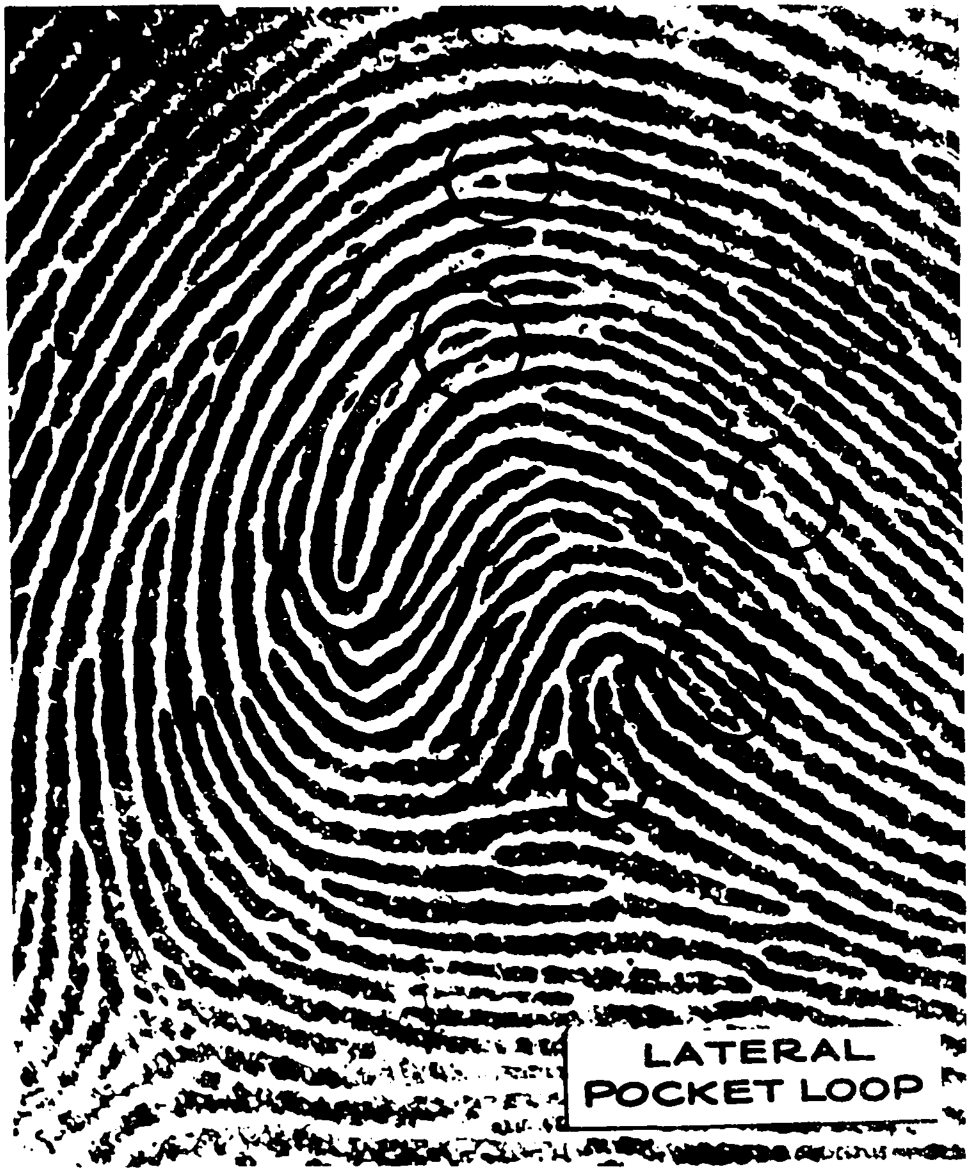


Figure B-3

Figure B-4

Figure B-5

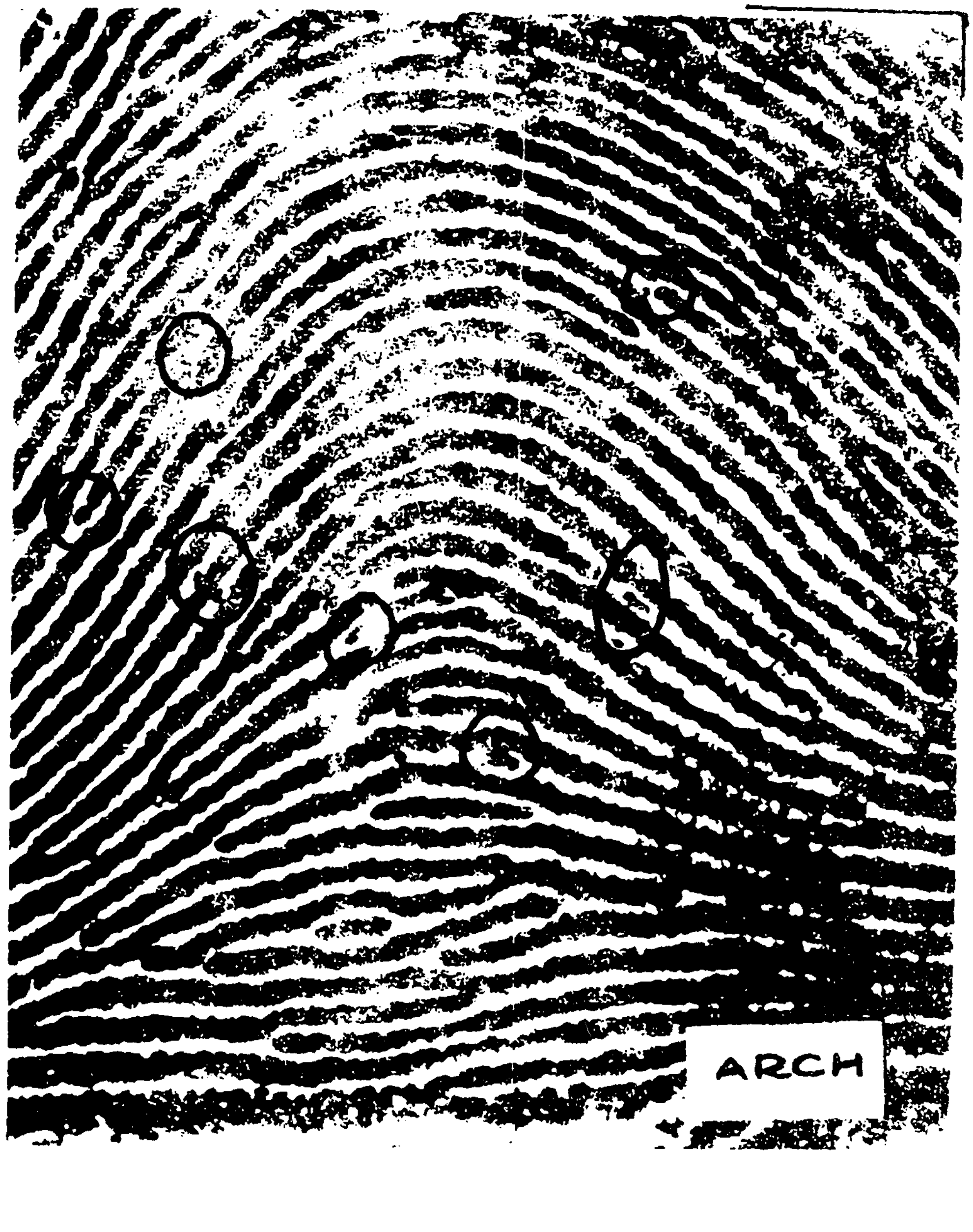


Figure B-6

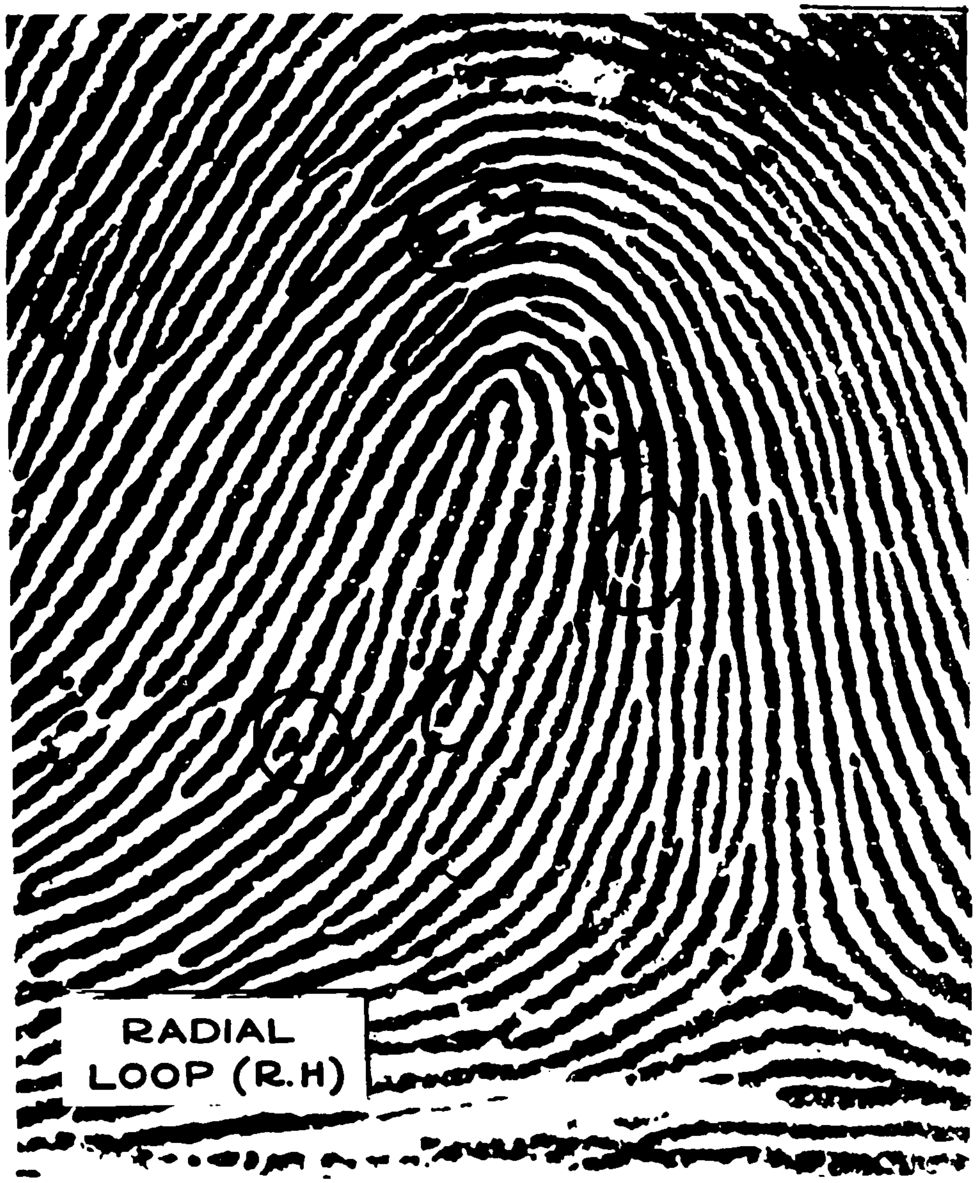


Figure B-7

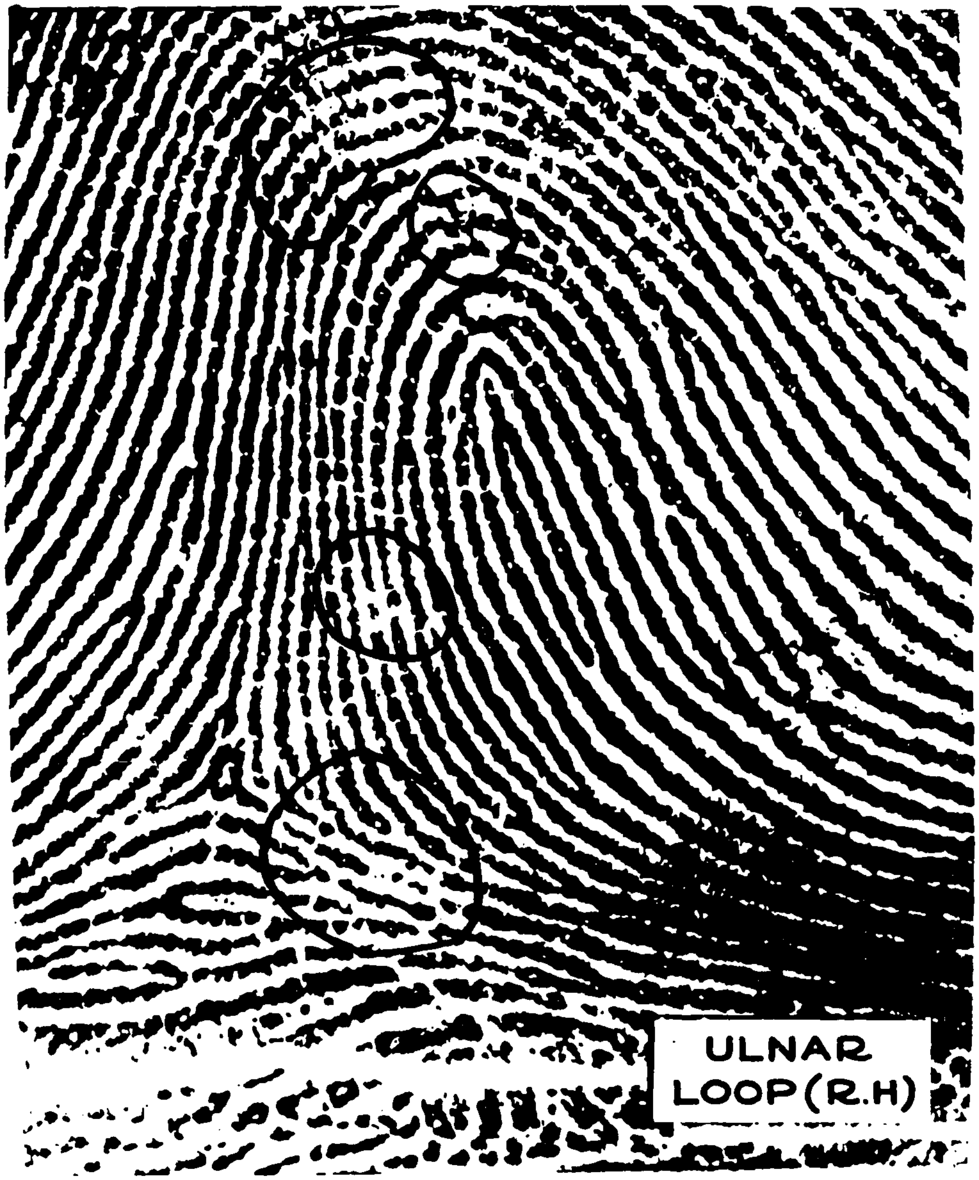


Figure B-8

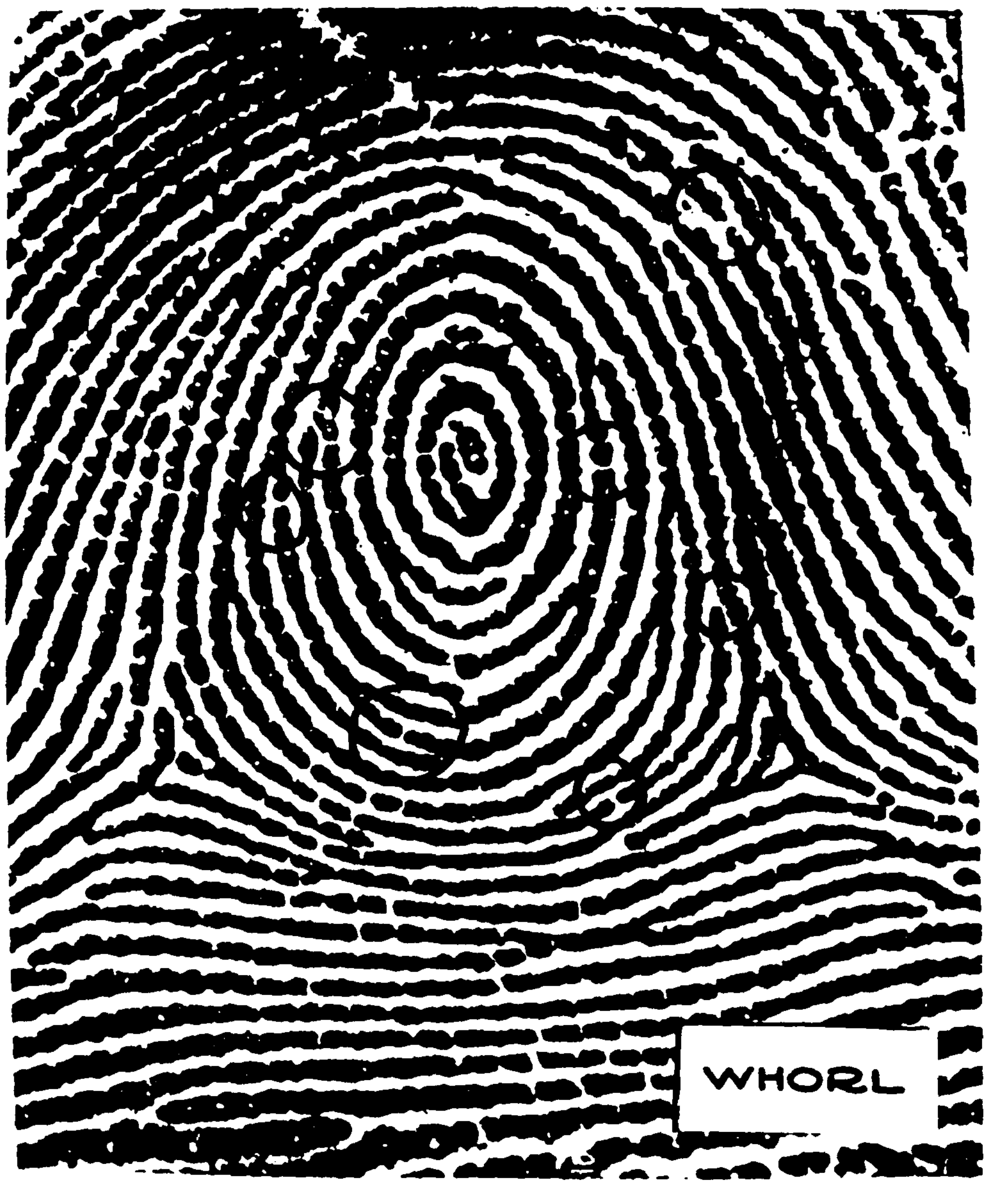


Figure B-9

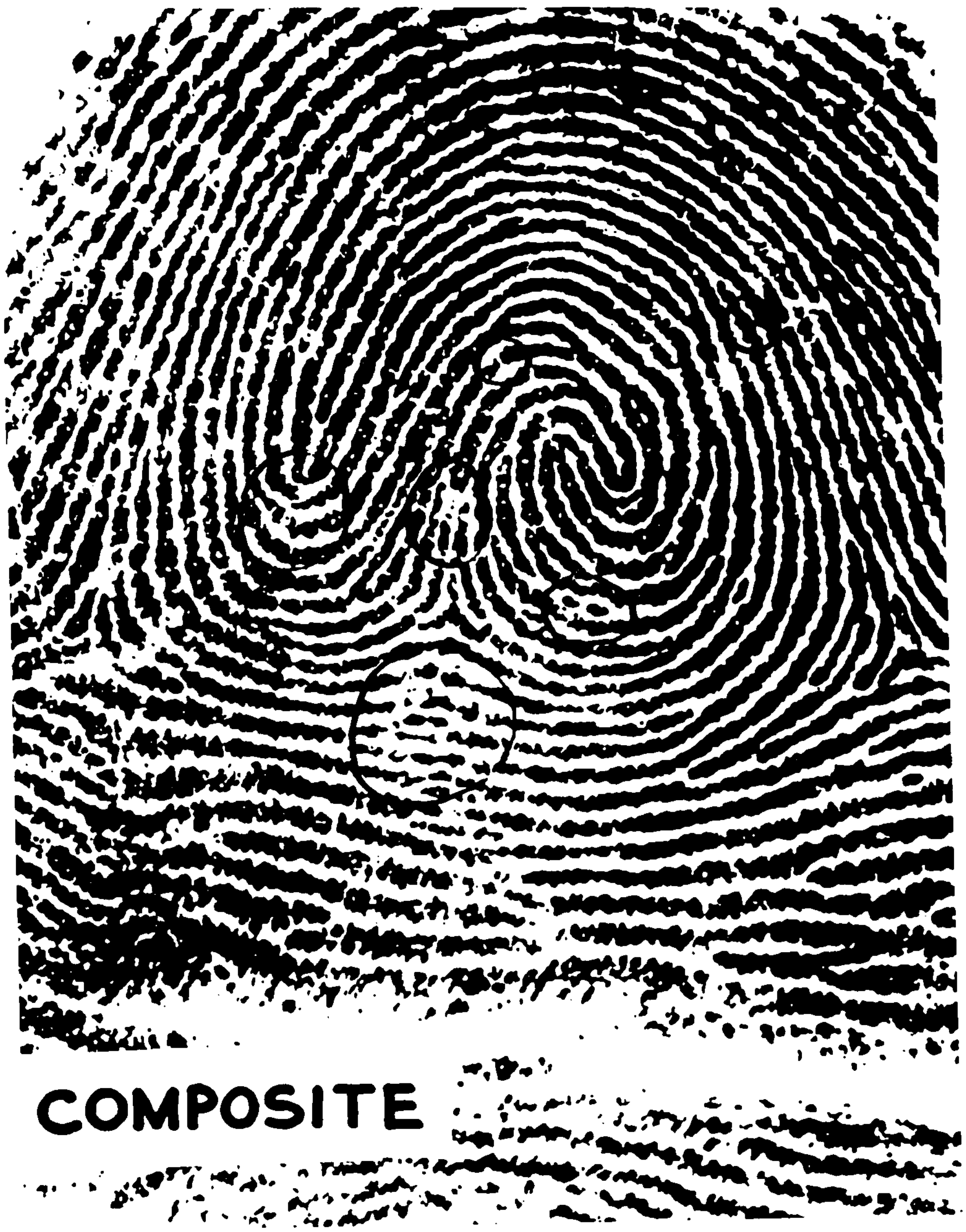


Figure B-10

APPENDIX C

This appendix contains the results of the manual examination of the Rabinow Electronics method

Figure C-1

Figure C-1

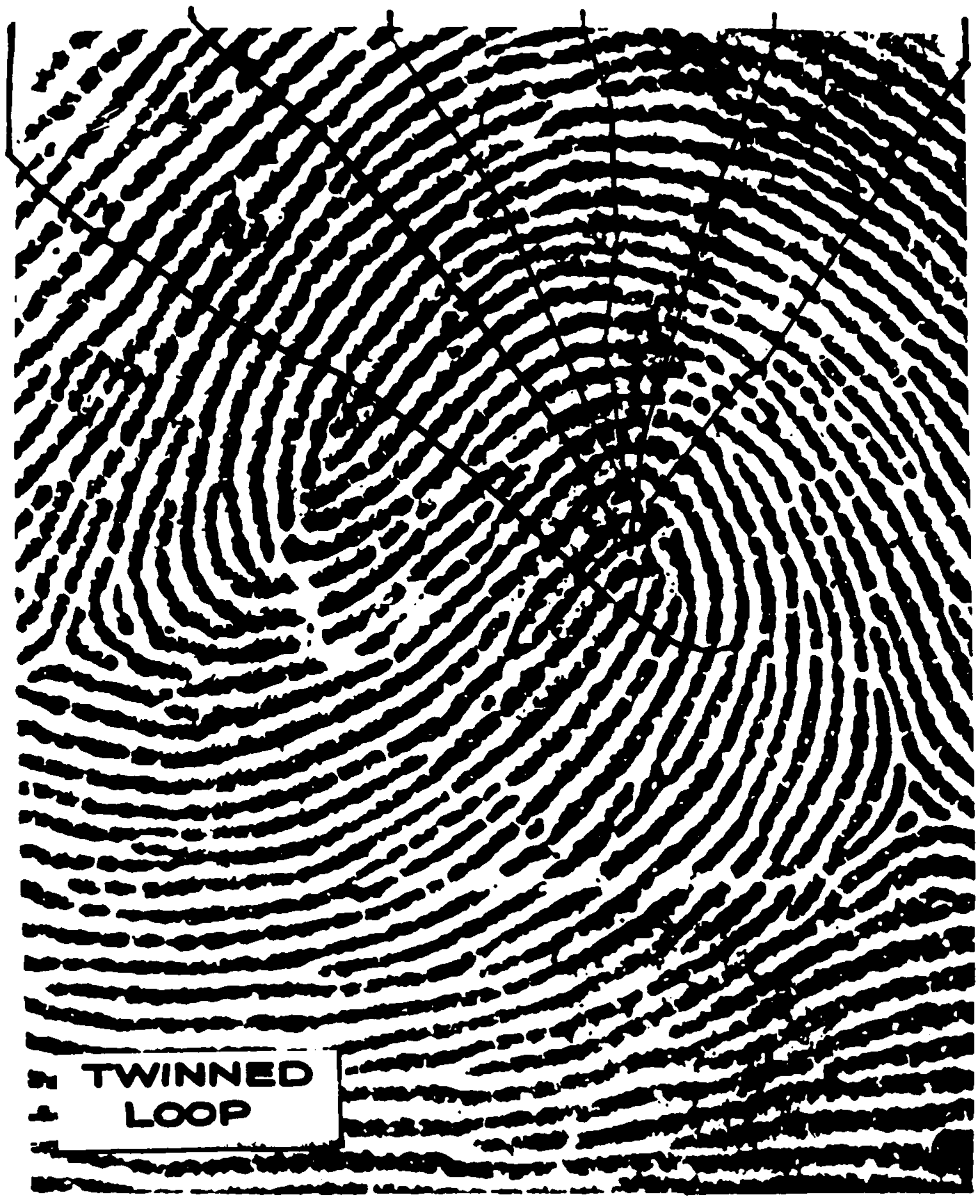


Figure C-2.1

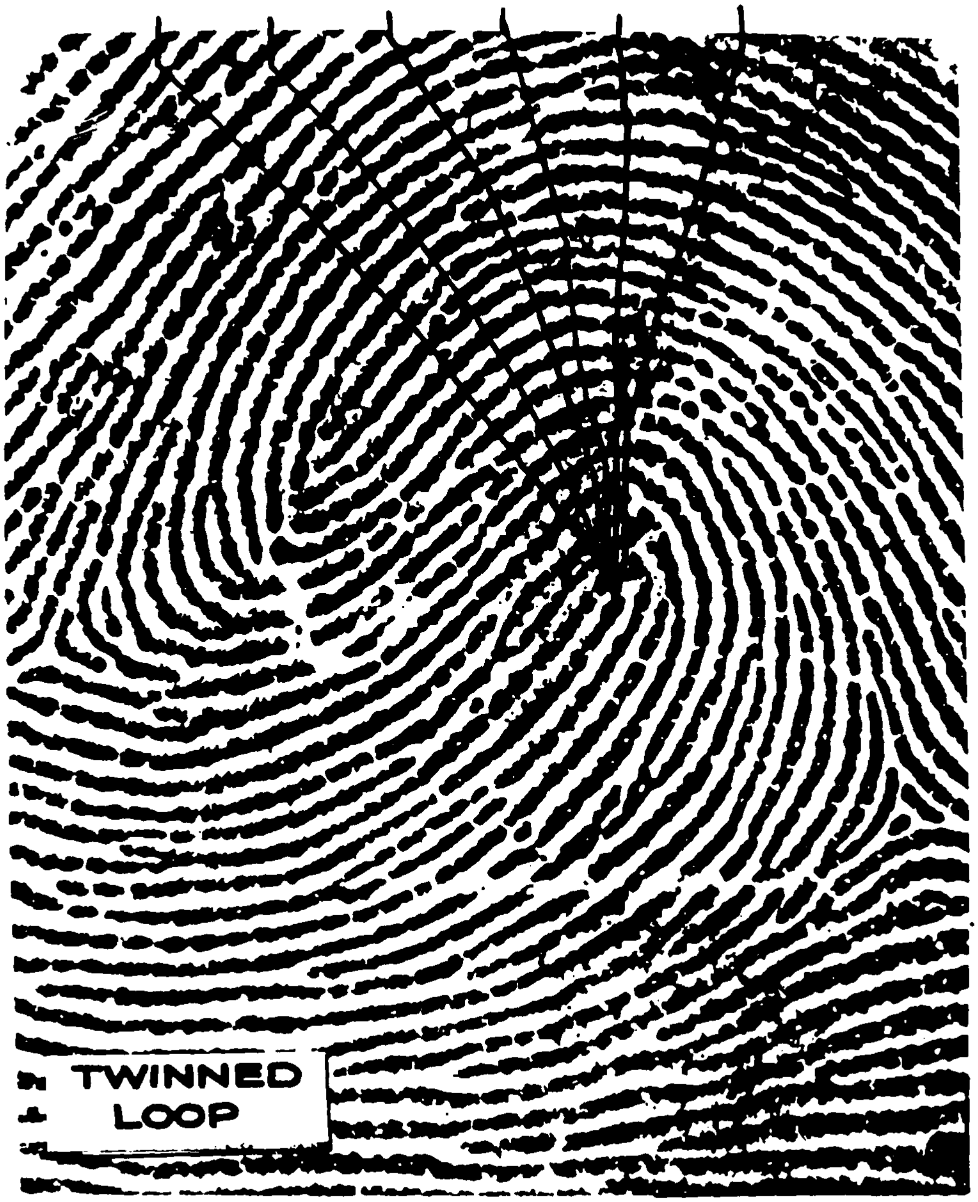


Figure C-2.2

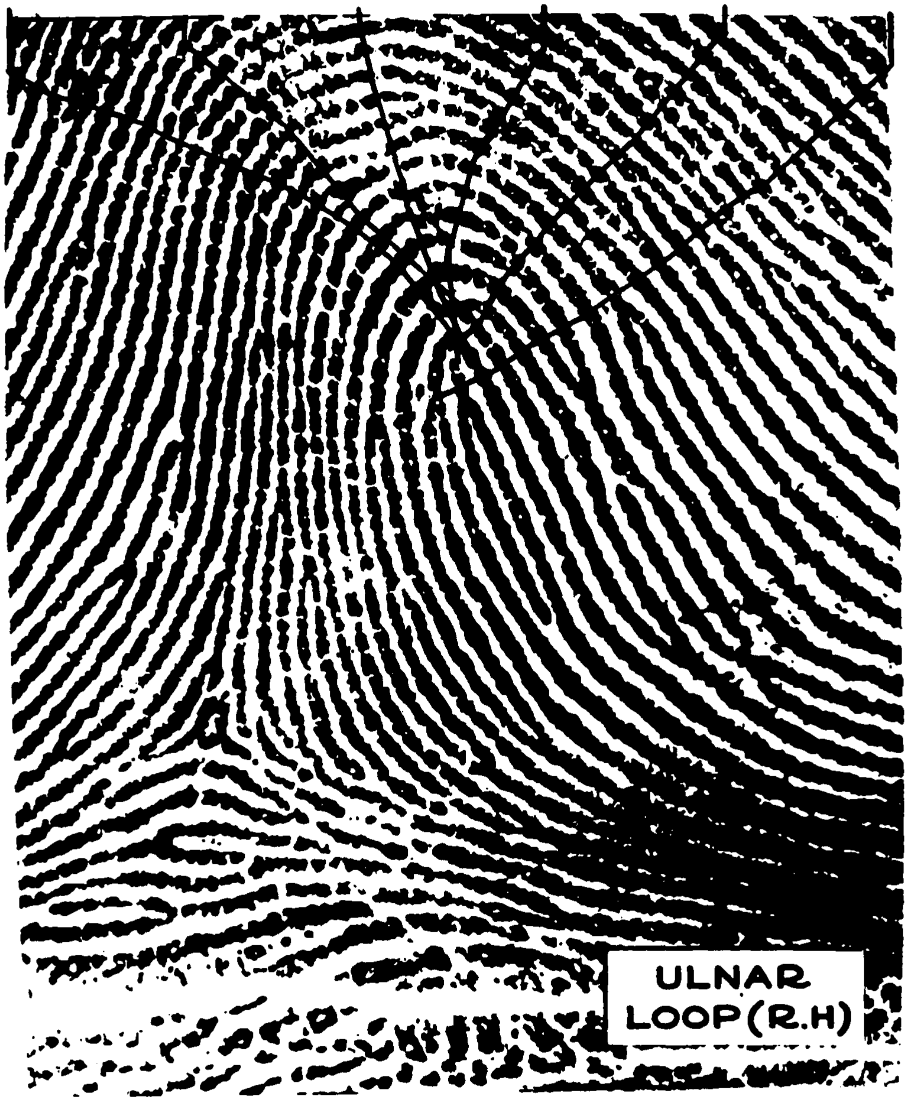


Figure C-3.1

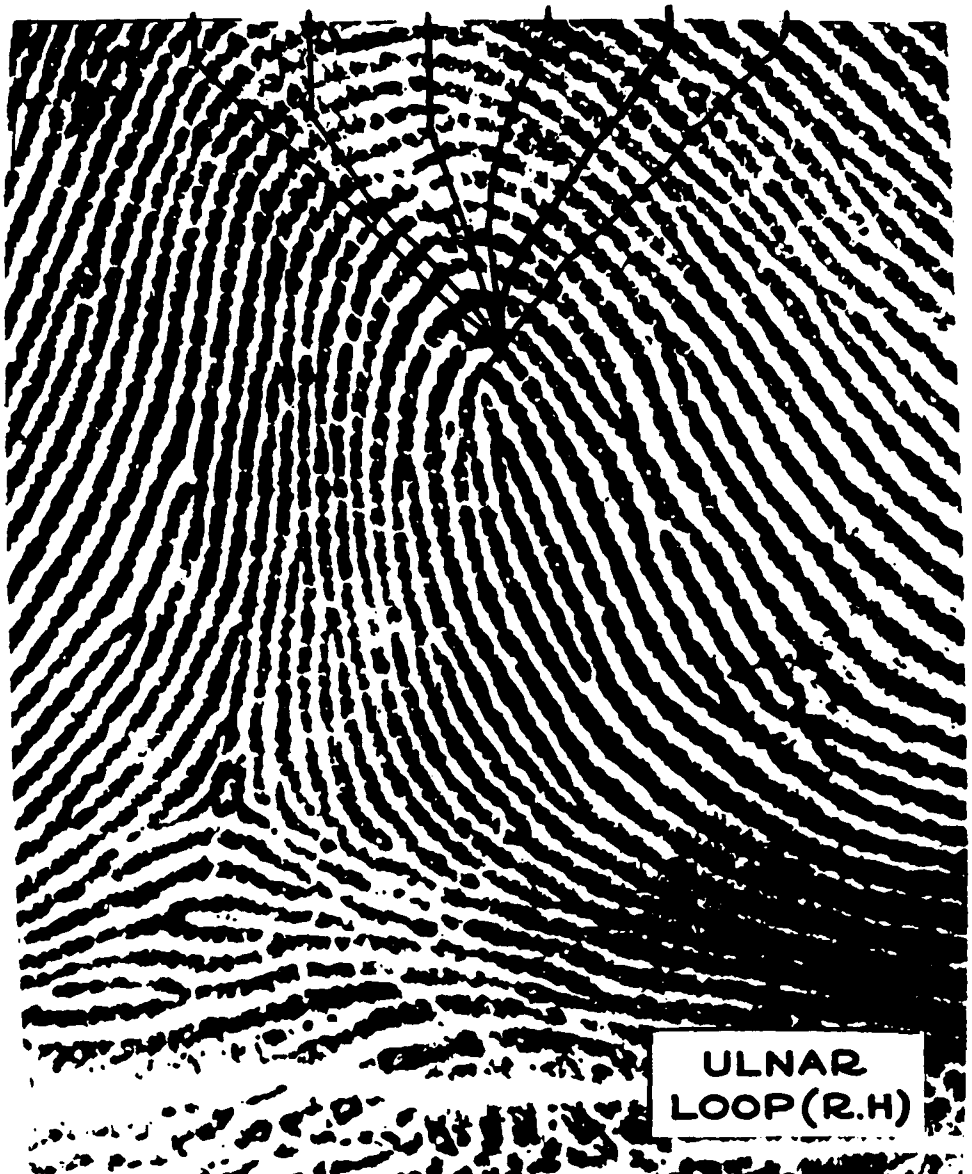


Figure C-3.2

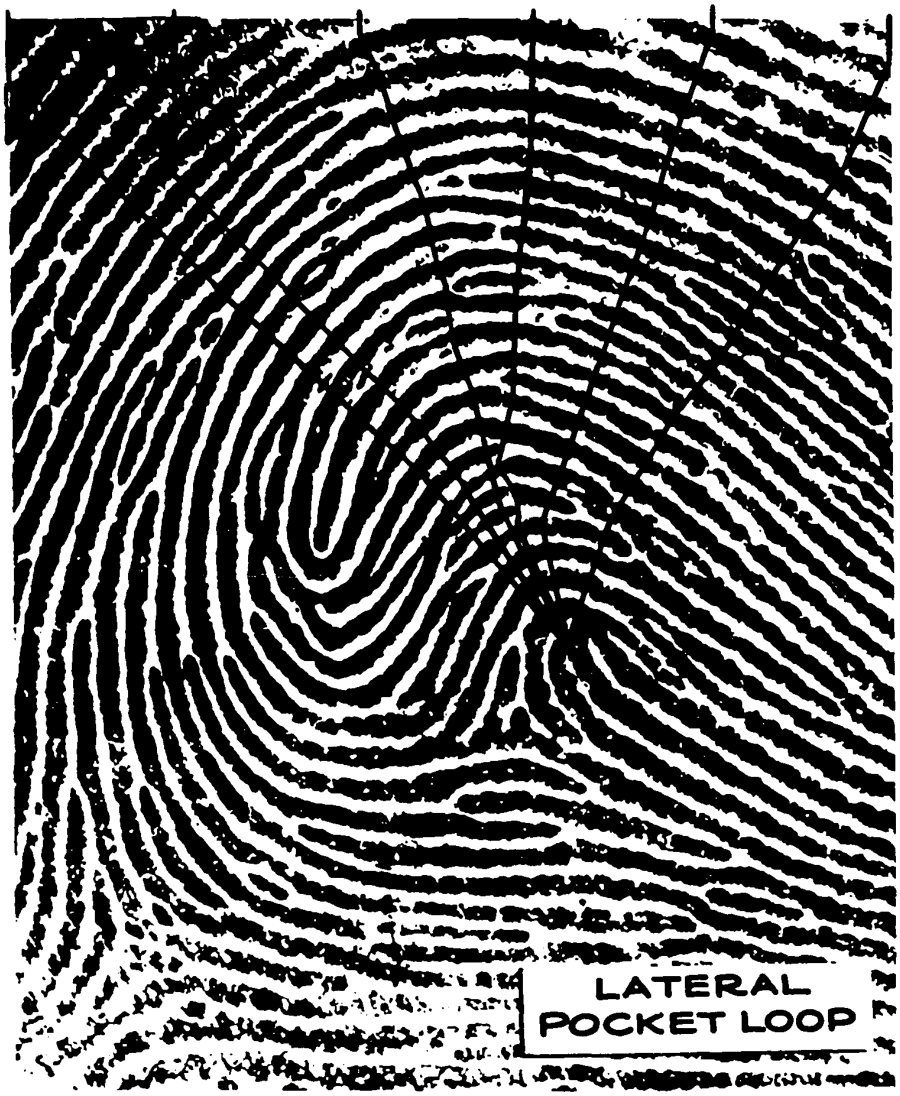


Figure C-4

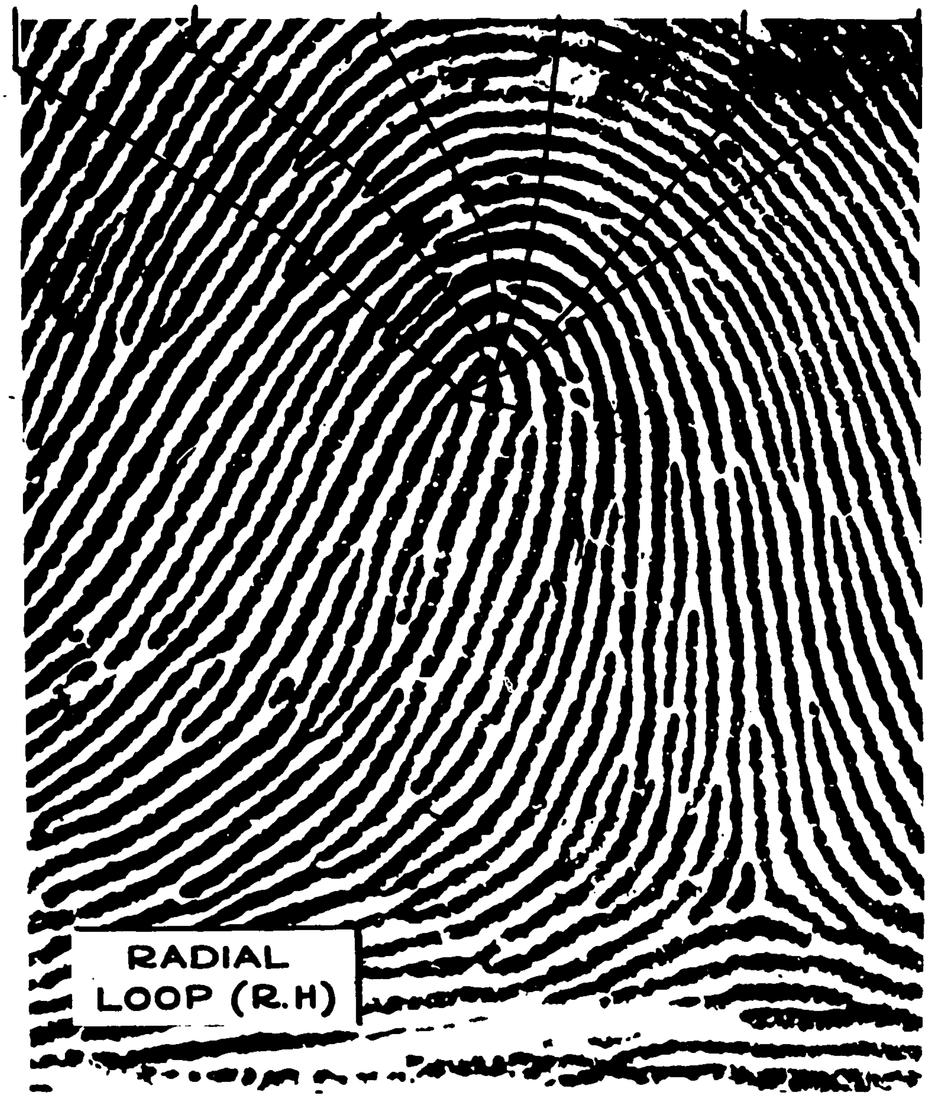


Figure C-5.1

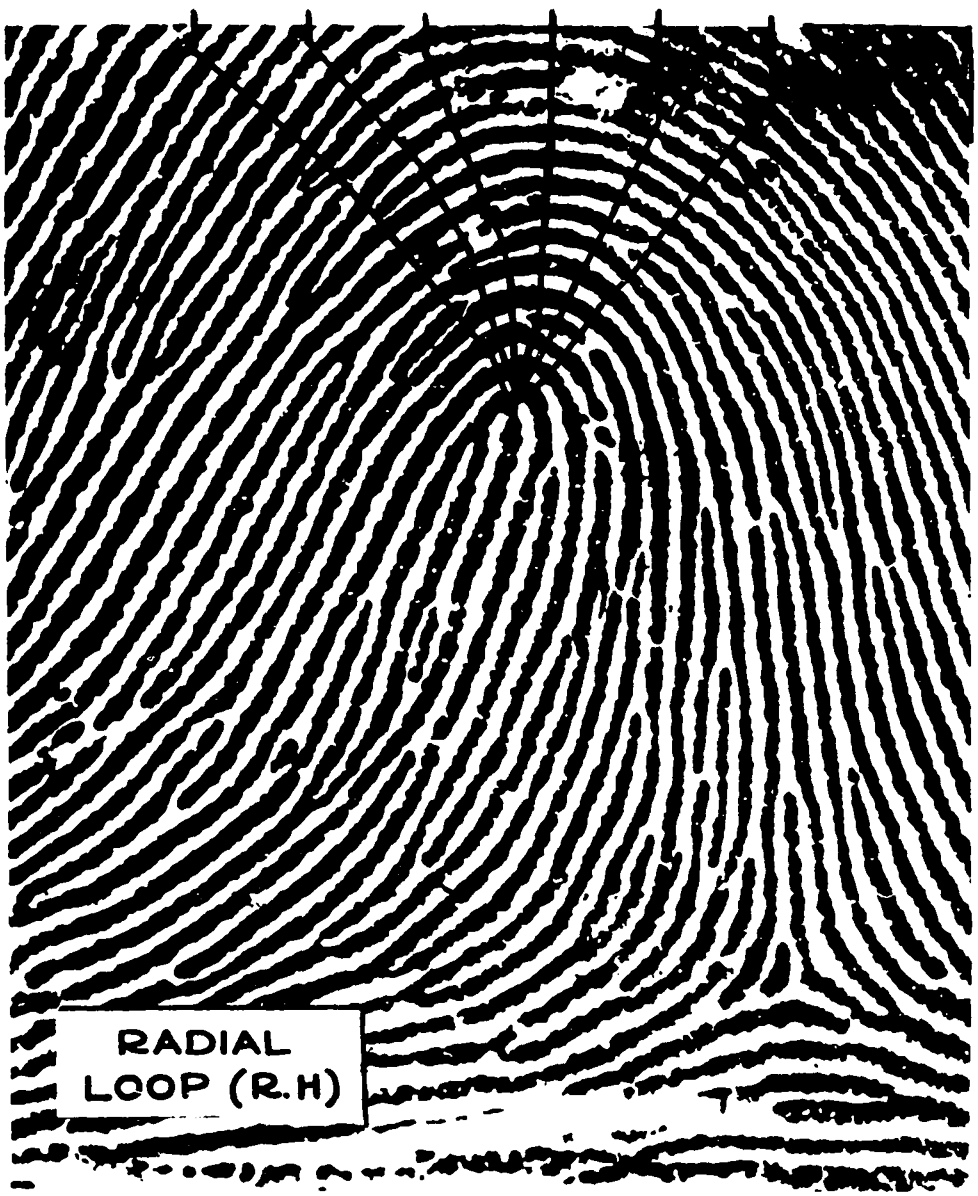


Figure C-5.2

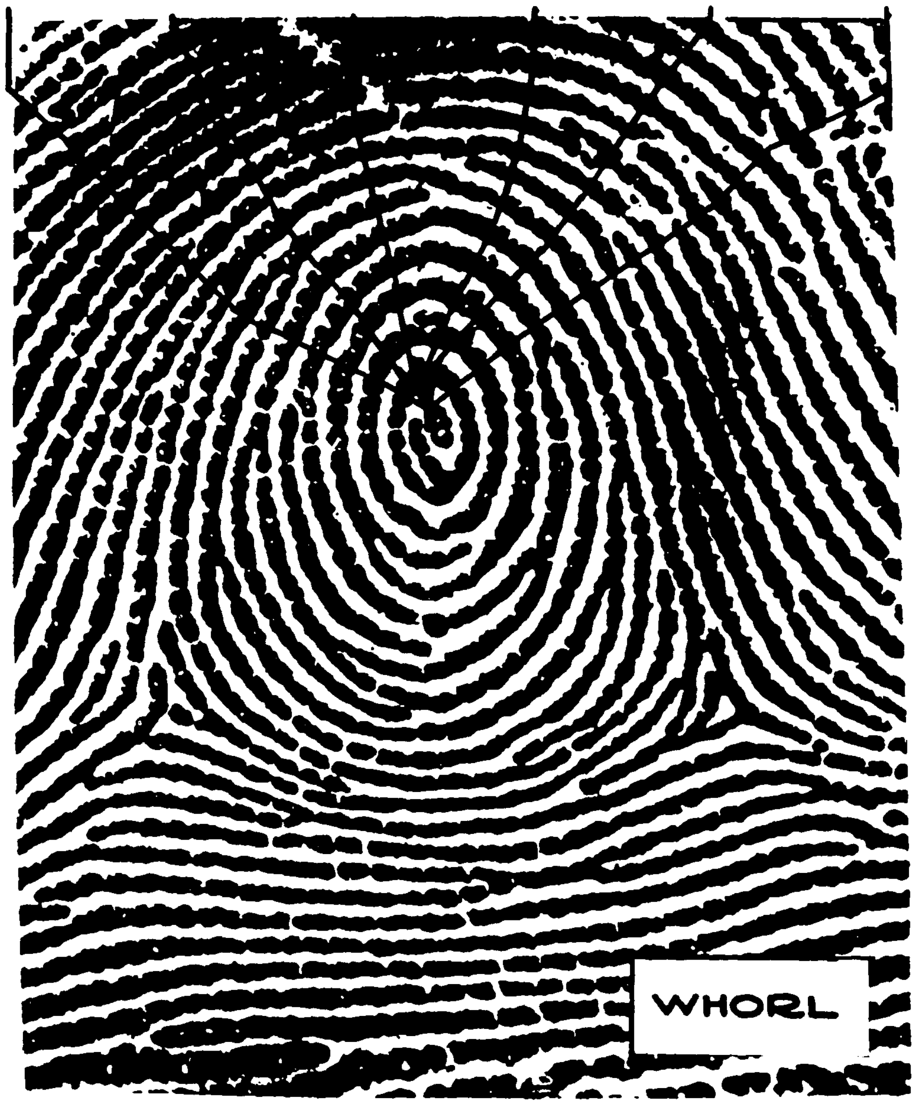


Figure C-6

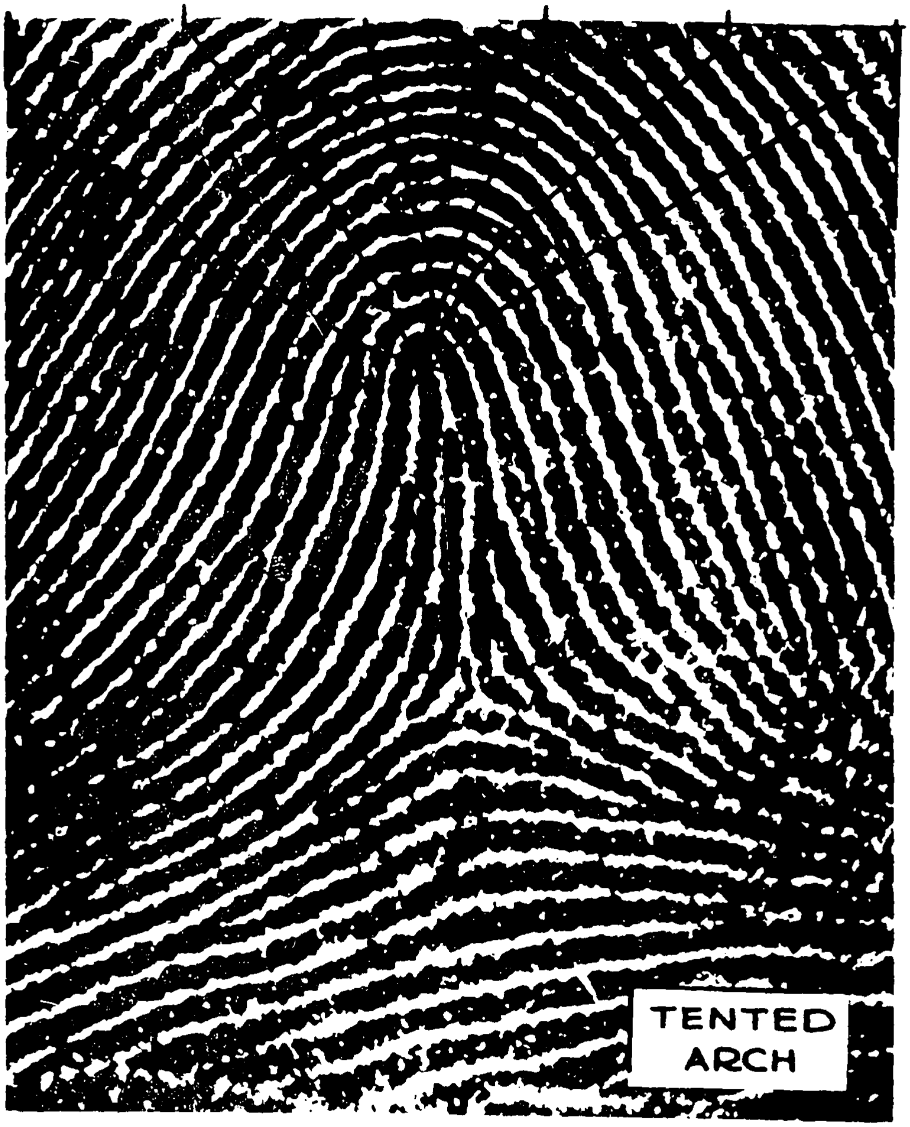


Figure C-7

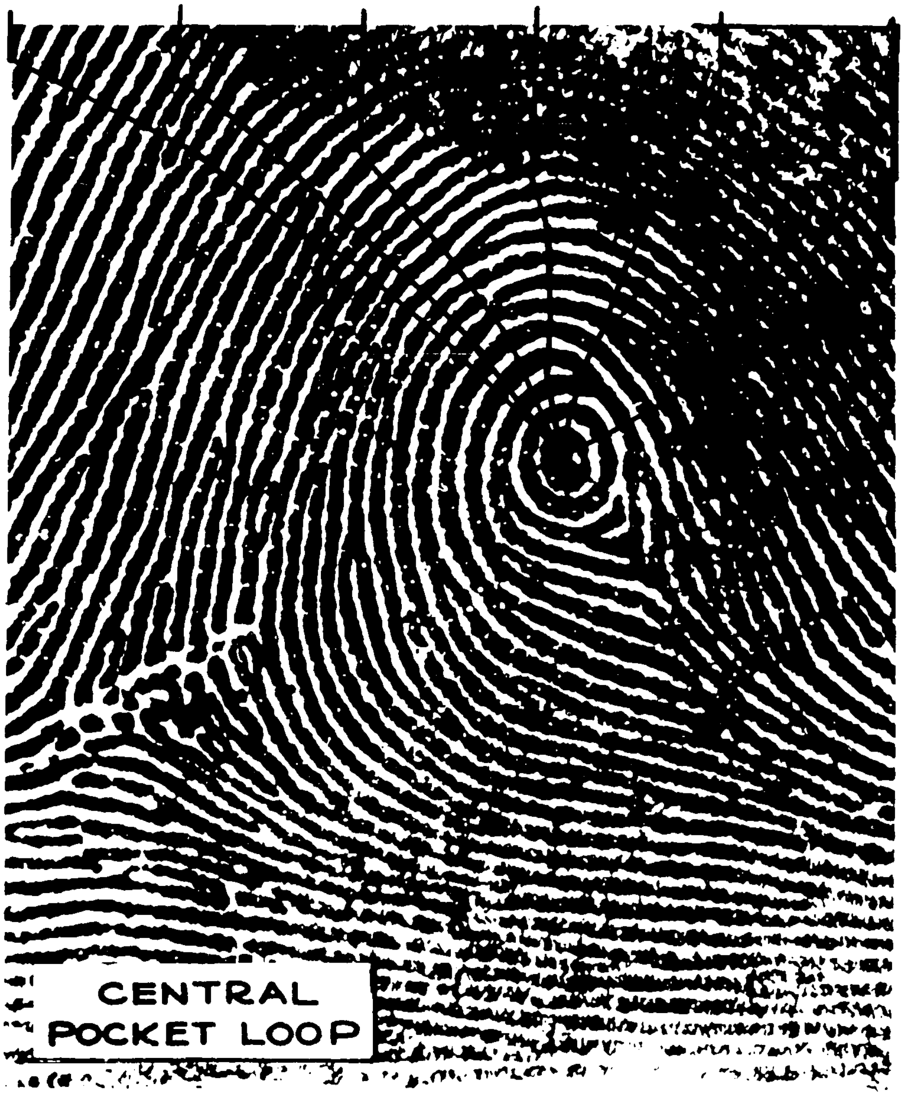


Figure C-8

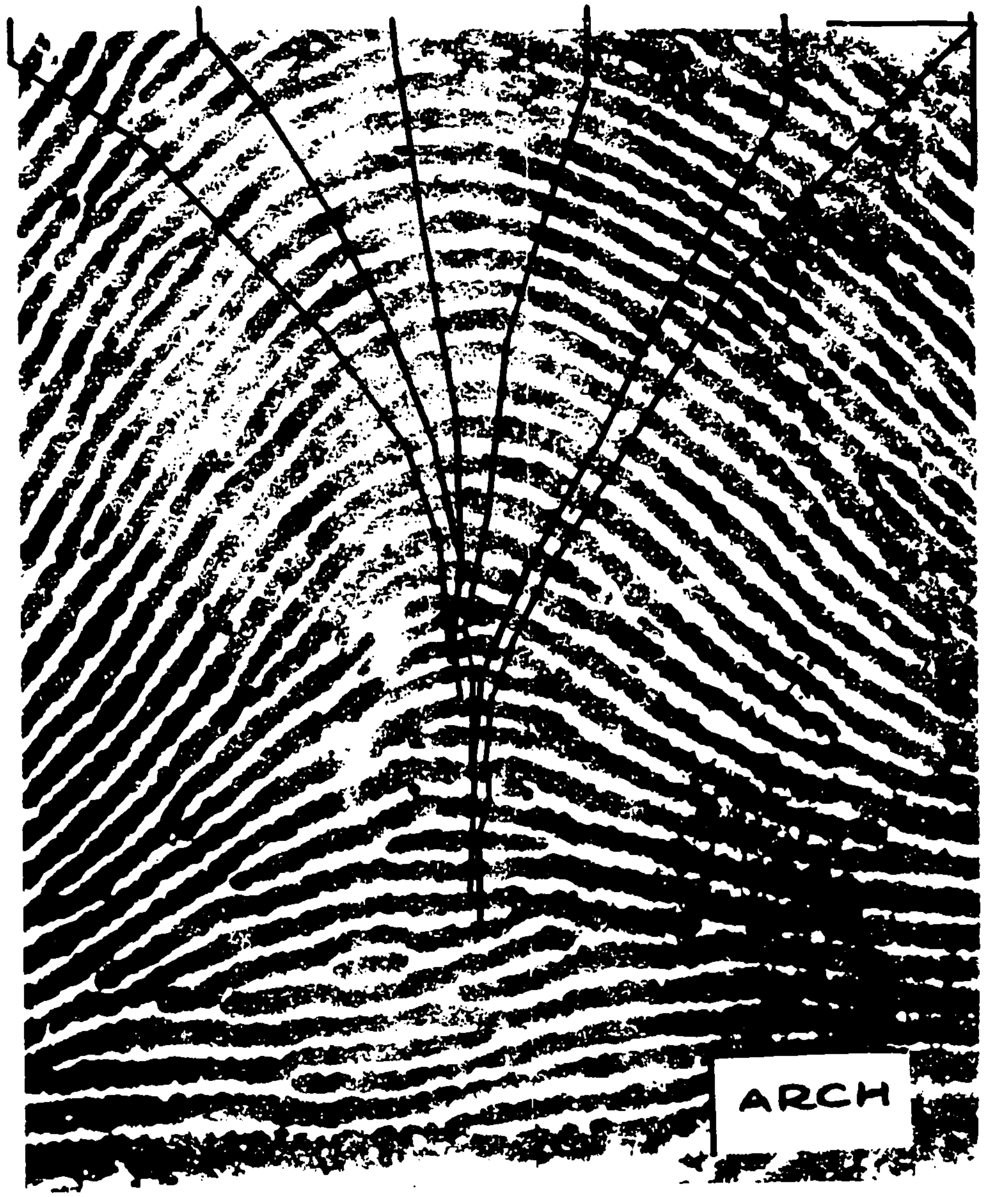


Figure C-9.1

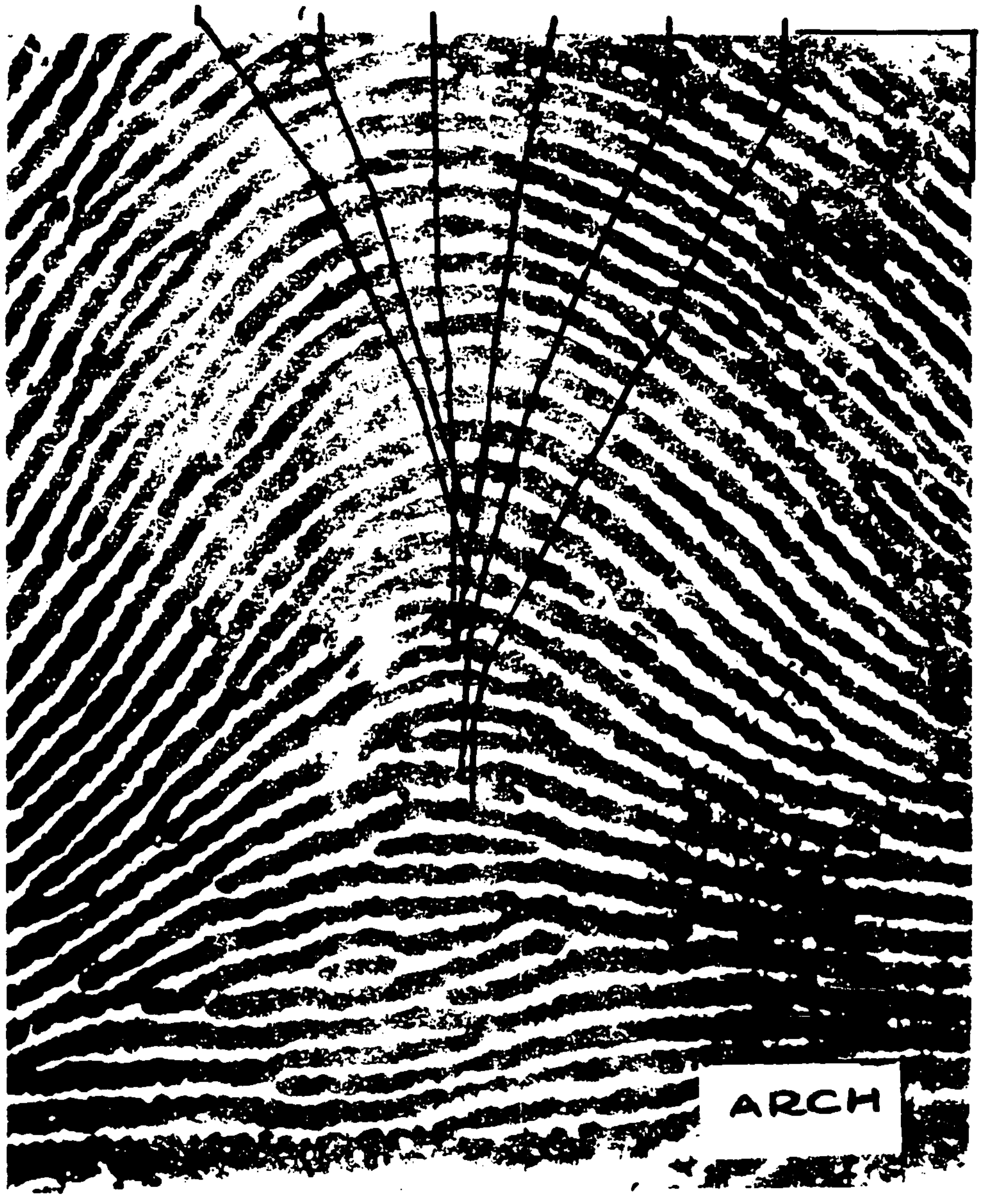


Figure C-9.2

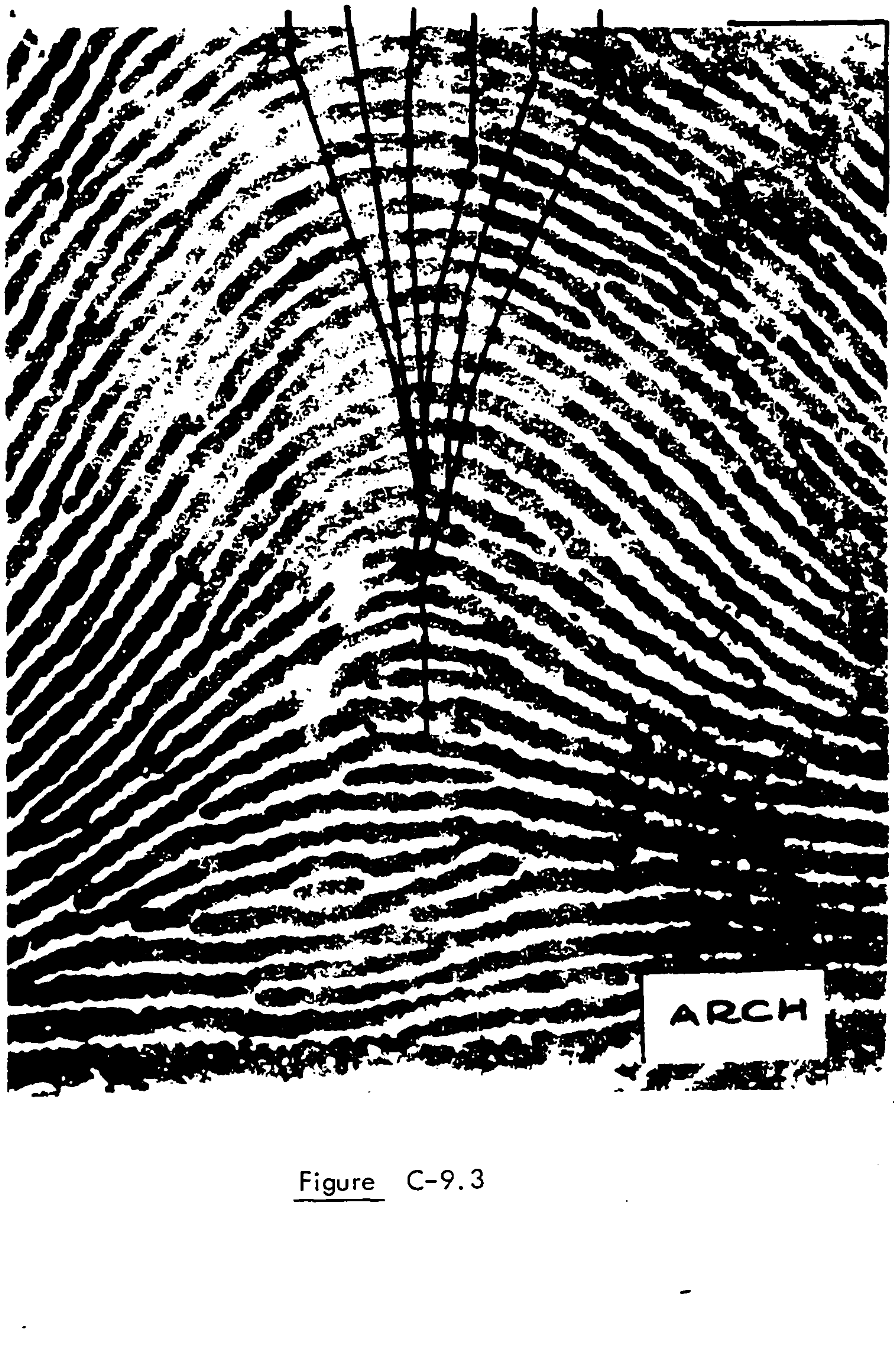


Figure C-9.3

Figure C-9.4

Figure C-10

APPENDIX D

The way one generates a 'ruler' and a partition for the purposes of intersection analysis depends on the way one generates the segmented trajectories. The author generated one segment of each trajectory sequentially, as pictured in Figure D.1.

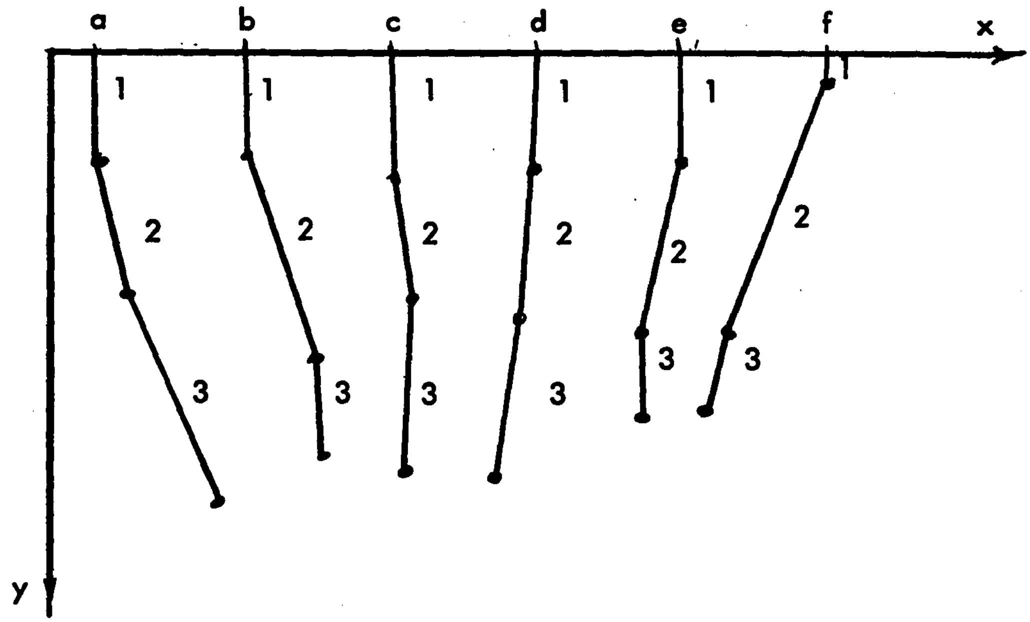


Figure D.1 Sequential Generation of Trajectories

That is, the segment labelled 1 is generated first on trajectories A through F. Then segment 2 is generated, and so on. The method the author used for setting up a ruler and partition for this type of trajectory generation is as follows:

(1) Initially set the ruler parallel to the x-axis at the origins of the trajectories and then generate segment 1 of the trajectories. (Figure D.2.) The points labelled G on trajectories A through F are the defining end points of the segments just generated and will be considered the generating points of the next segments.

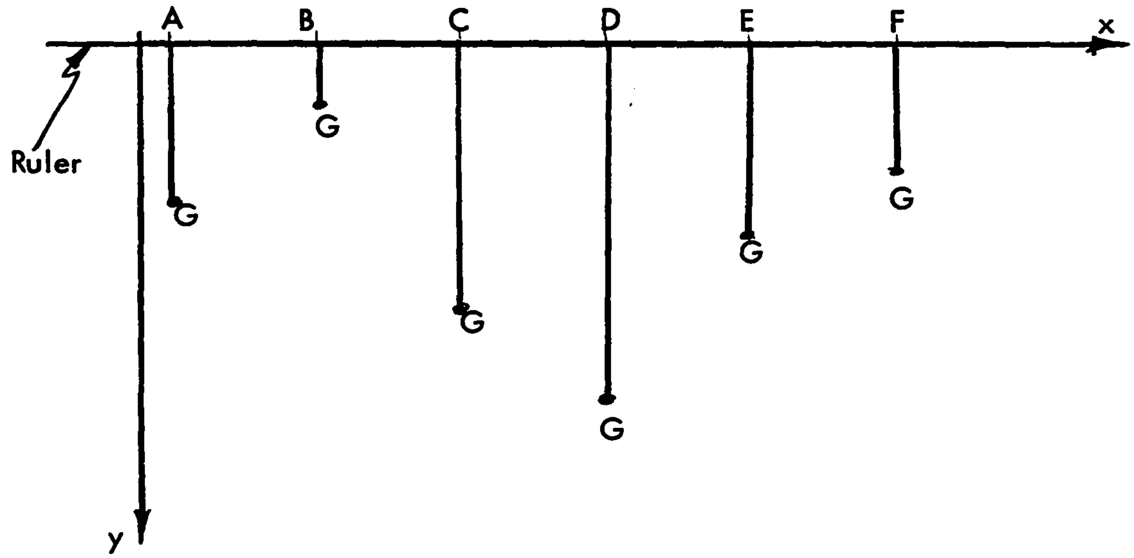


Figure D.2 Generation of First Segments

(2) Examine all segements of the trajectories that lie in the partition above the ruler ($y > y$ ruler) for intersections. After the analysis, move the ruler to the generating point having the smallest y value; in this case point G of trajectory B. (Figure D.3.)

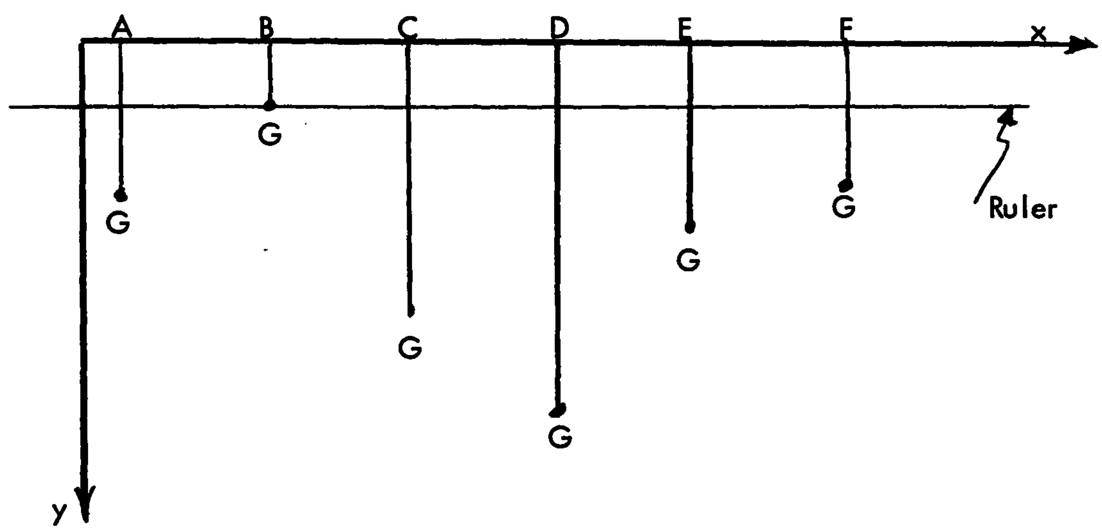


Figure D.3 Moving the Ruler

The reason for this placement of the ruler is that further comparisons (according to rule 2) of other segments as they are generated will be sure to find any intersections that occur. For example, (see Figure D.4) if the ruler was placed at position z instead of position v, and segment 2 of trajectory B was generated as shown, no intersection would be found, since one only searches in the partition above the ruler (y > y ruler). Therefore, the ruler is advanced only as fast as the smallest value of the generating points of the trajectories.

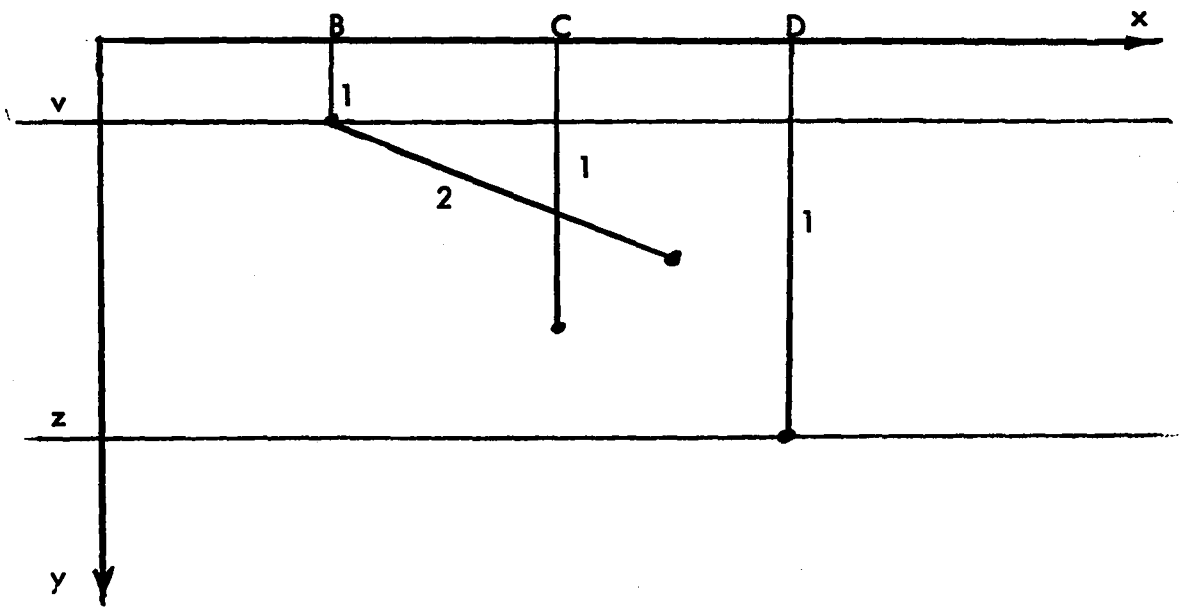


Figure D.4 Unlocated Crossing Between Trajectories B and C

APPENDIX E

MACHINE AND PROGRAM STATISTICS

MACHINE: IBM 360/75

System MVT release 16 and 17

PROGRAM:

Language	FORTRAN IV	
Length	43 K Bytes	
Running time	30 seconds for one complete analysis	
Average trajectory length	20 segments	
Group 1 fingerprints	18/150	12%
Group 2 fingerprints	108/150	72%
Group 3 fingerprints	24/150	16%
Total number of fingerprints with reference points	136/150	84%

The following pictures represent typical trajectories from the various groups of fingerprints.

Figure E.1 Group 1 Trajectories

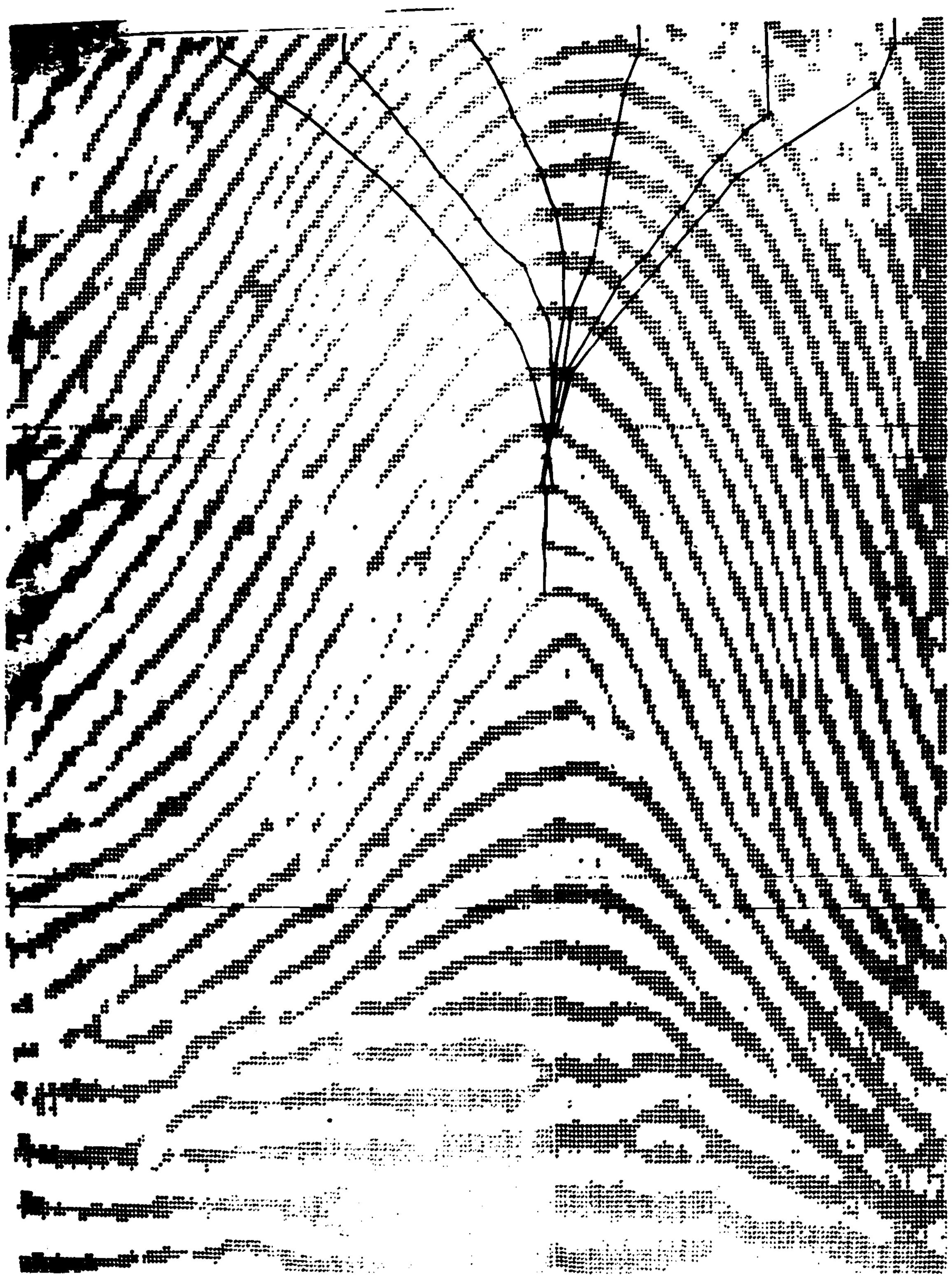


Figure E.2 Group 1 Trajectories

Figure E.3 Group 2 Trajectories

Figure E.4 Group 2 Trajectories

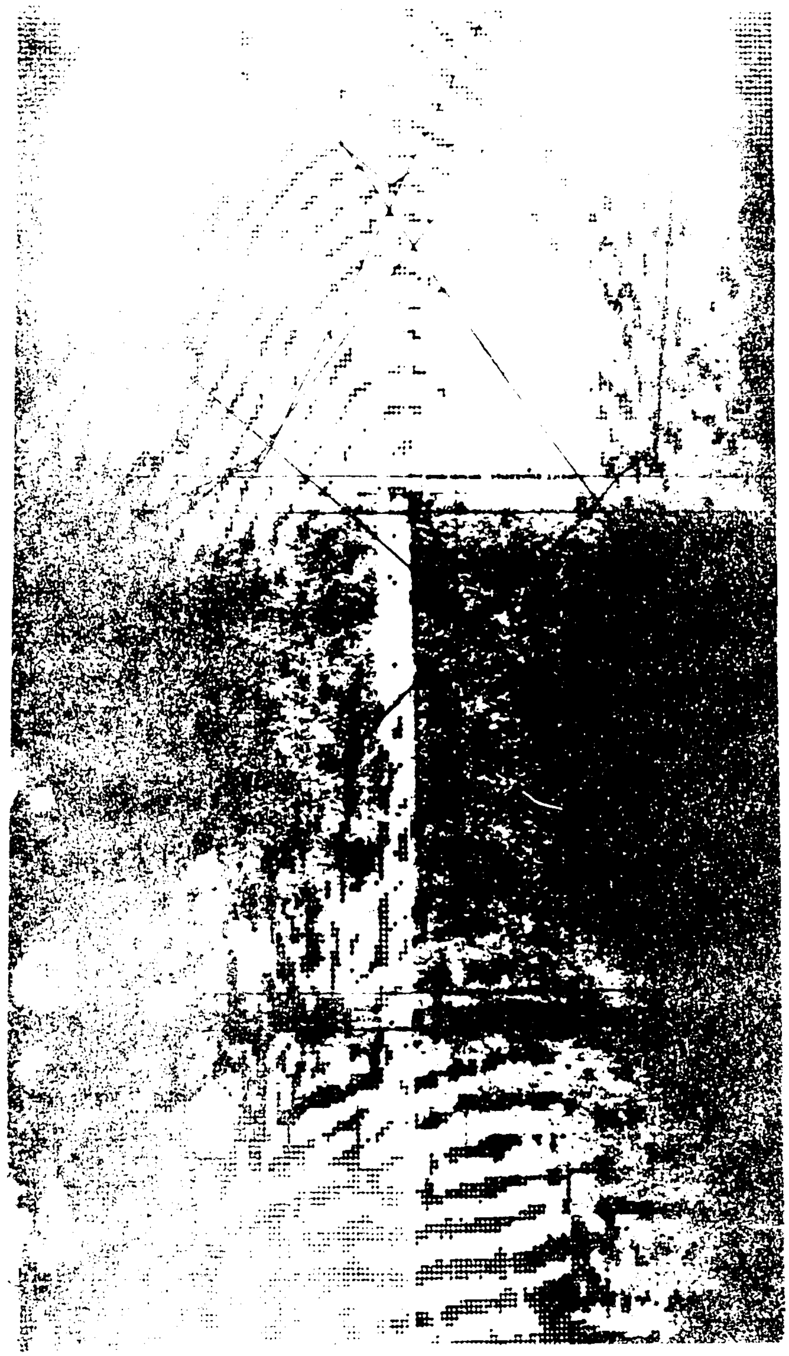


Figure E.6 Group 3 Trajectories

APPENDIX F

This appendix contains the results of the experiments carried out using the digital method

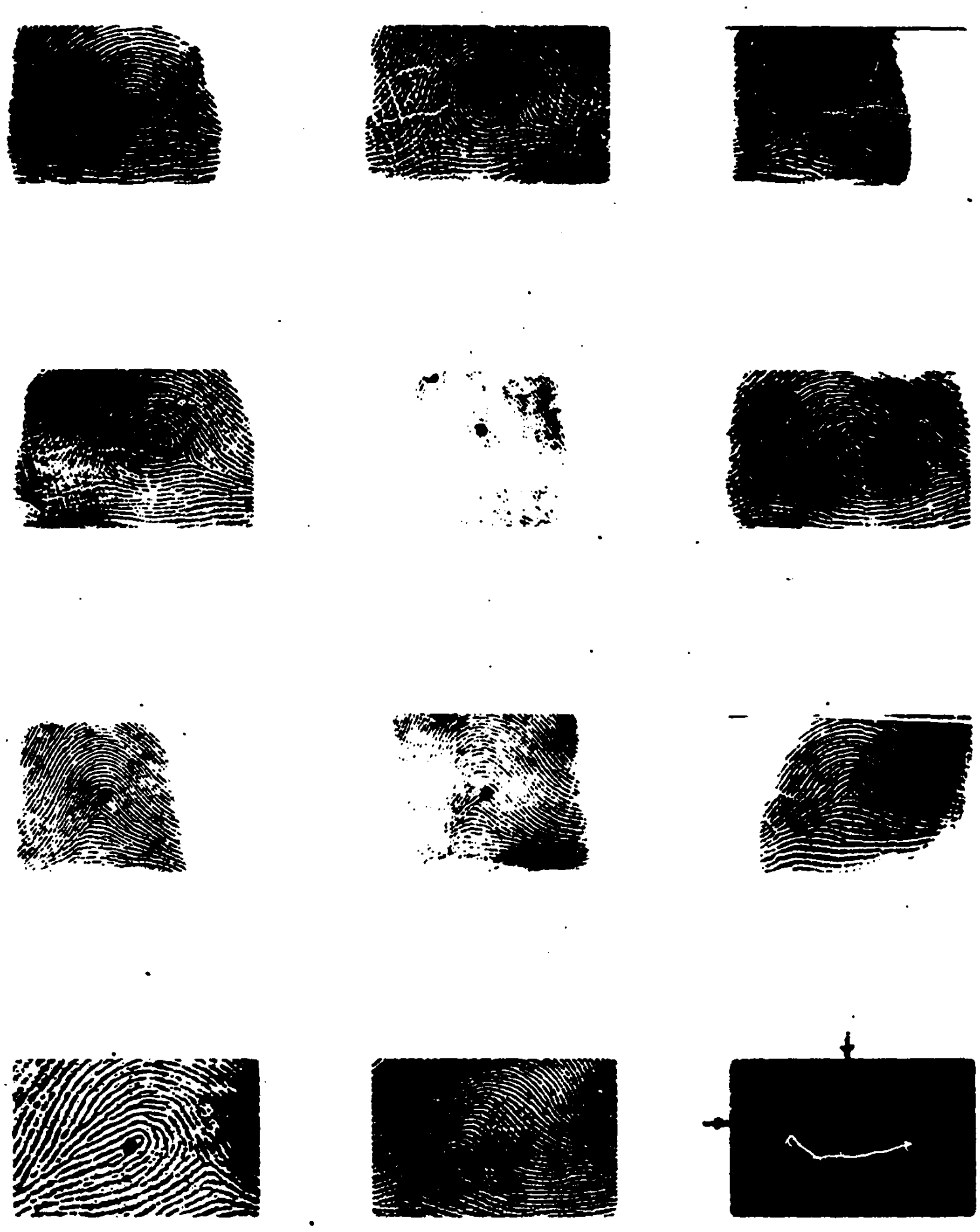


Plate 1

Plate 2

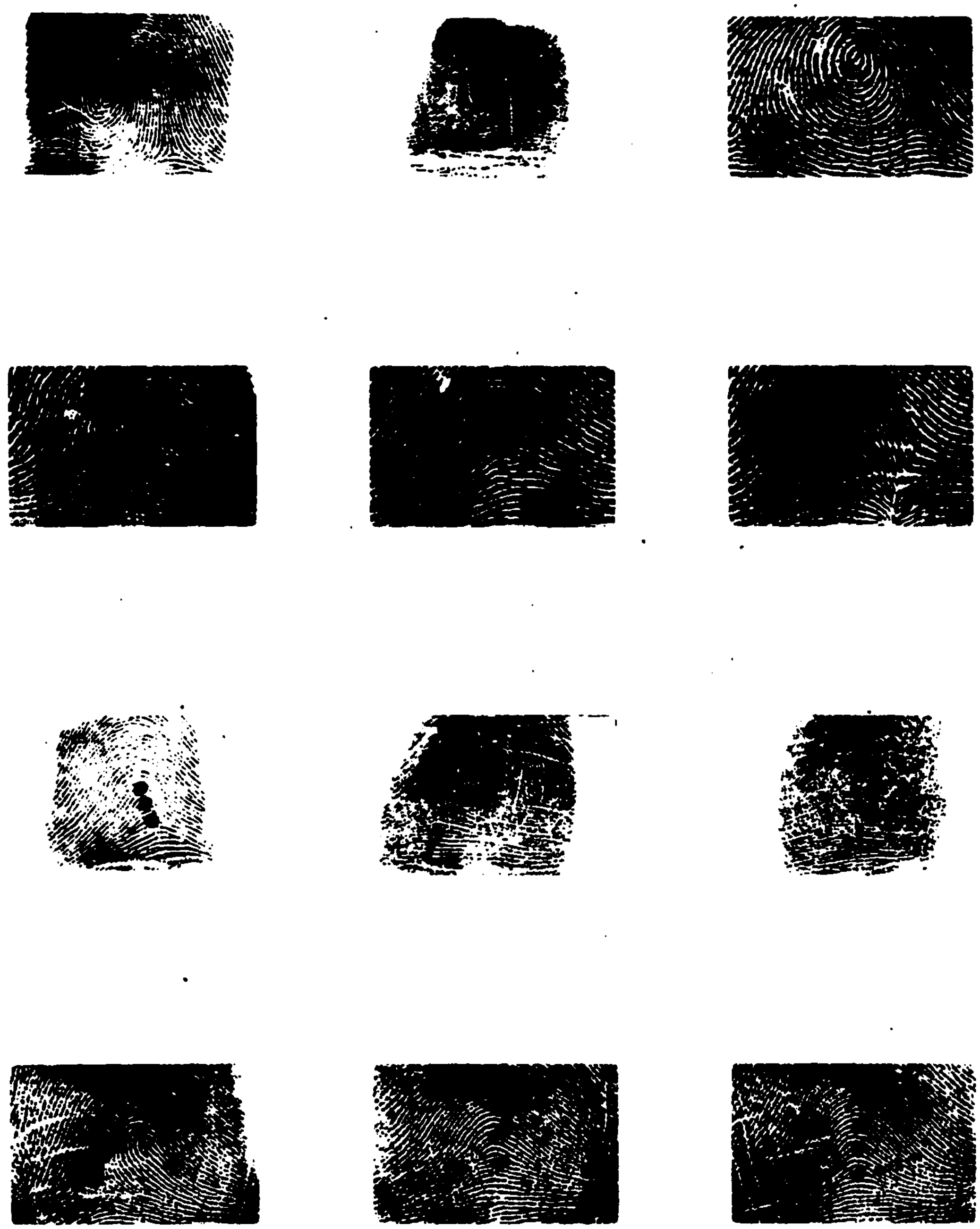


Plate 3

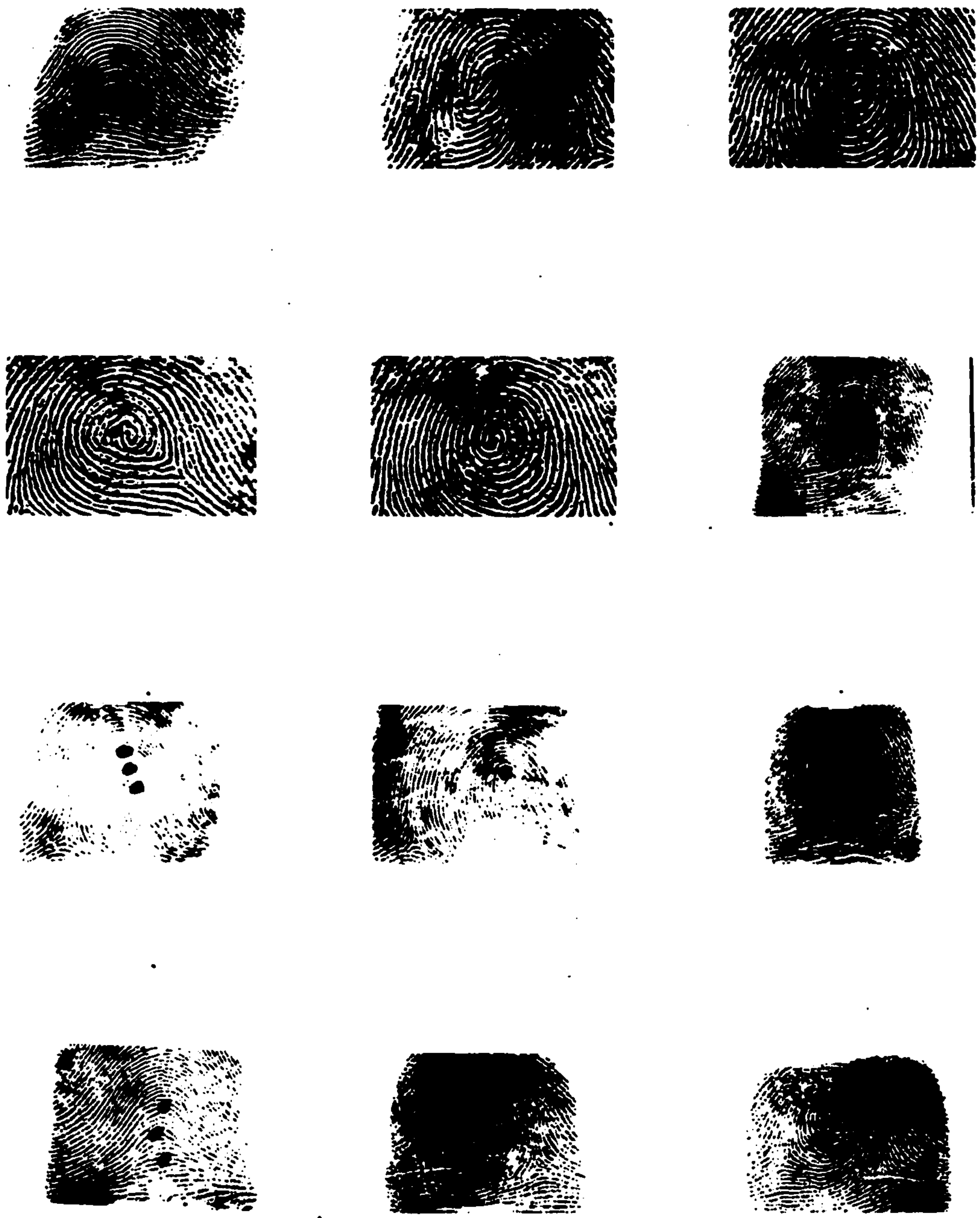


Plate 4

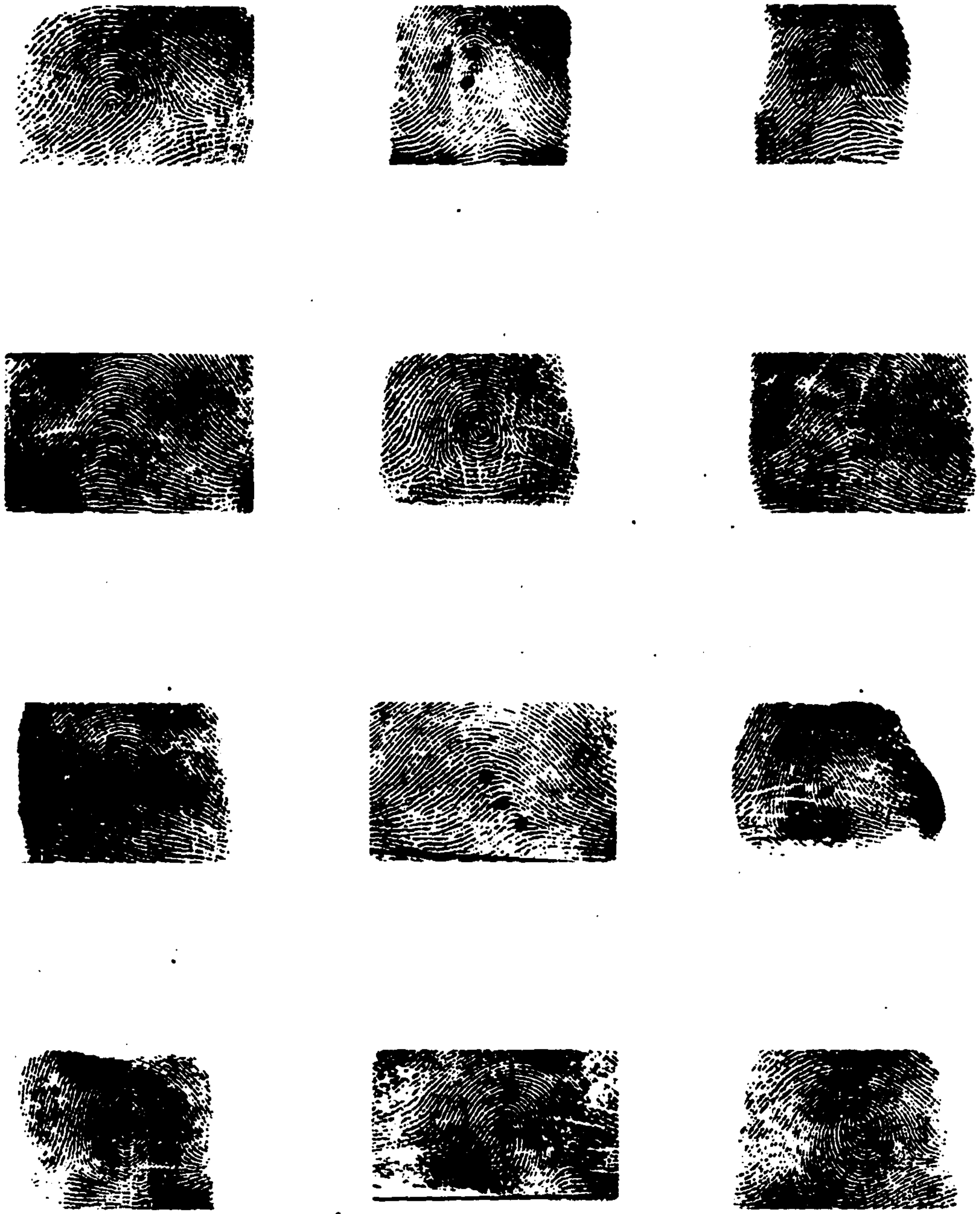


Plate 5

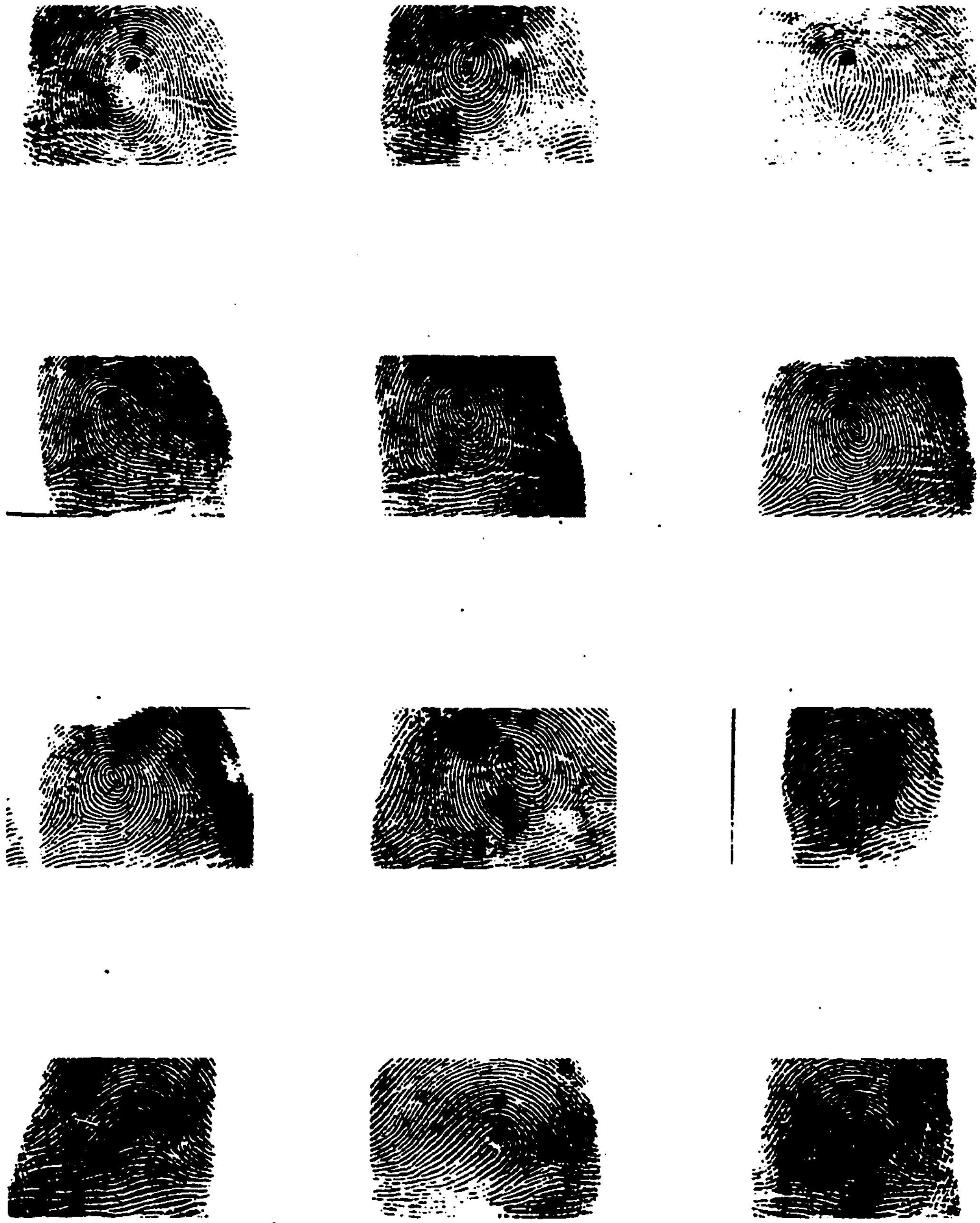


Plate 6

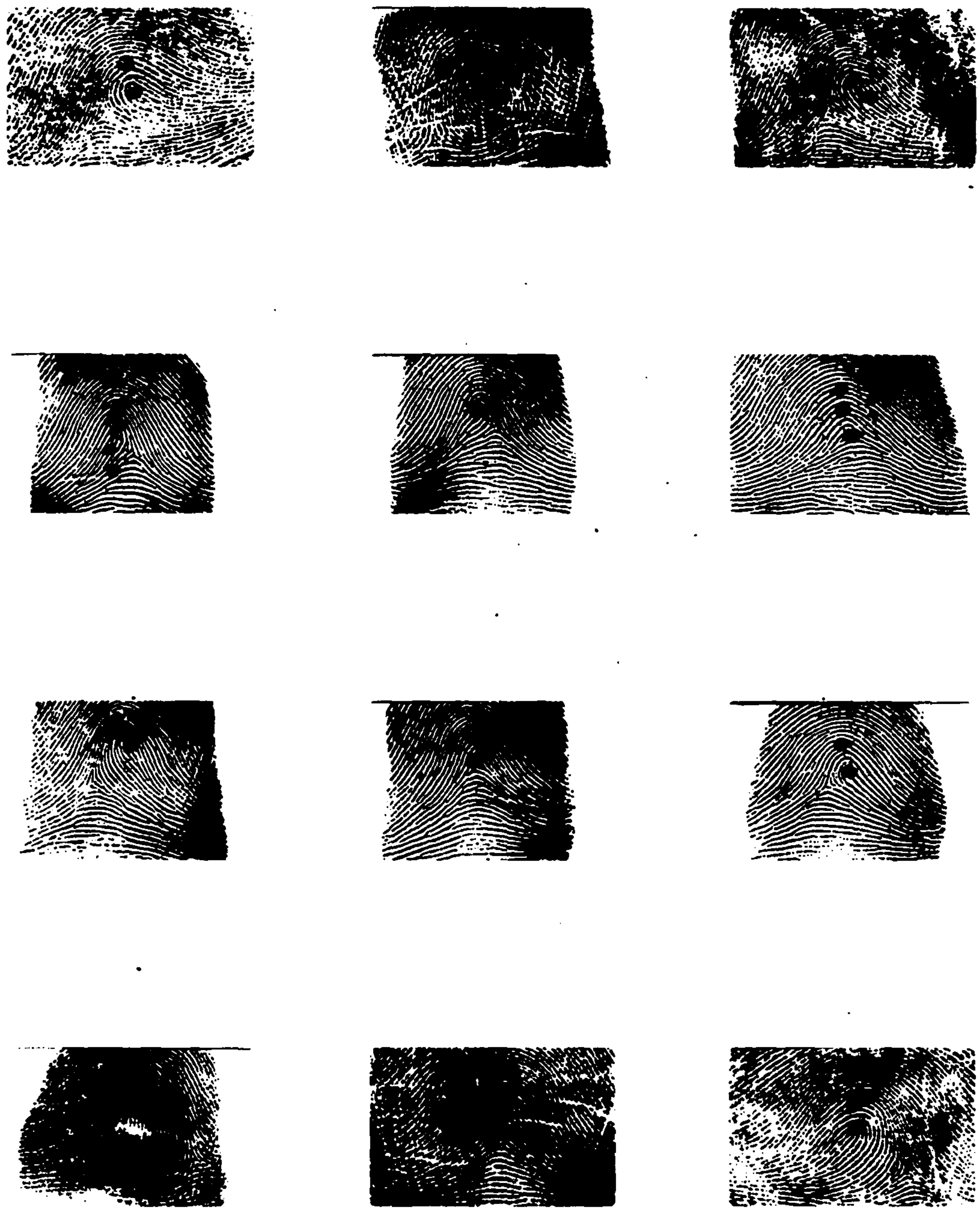


Plate 7

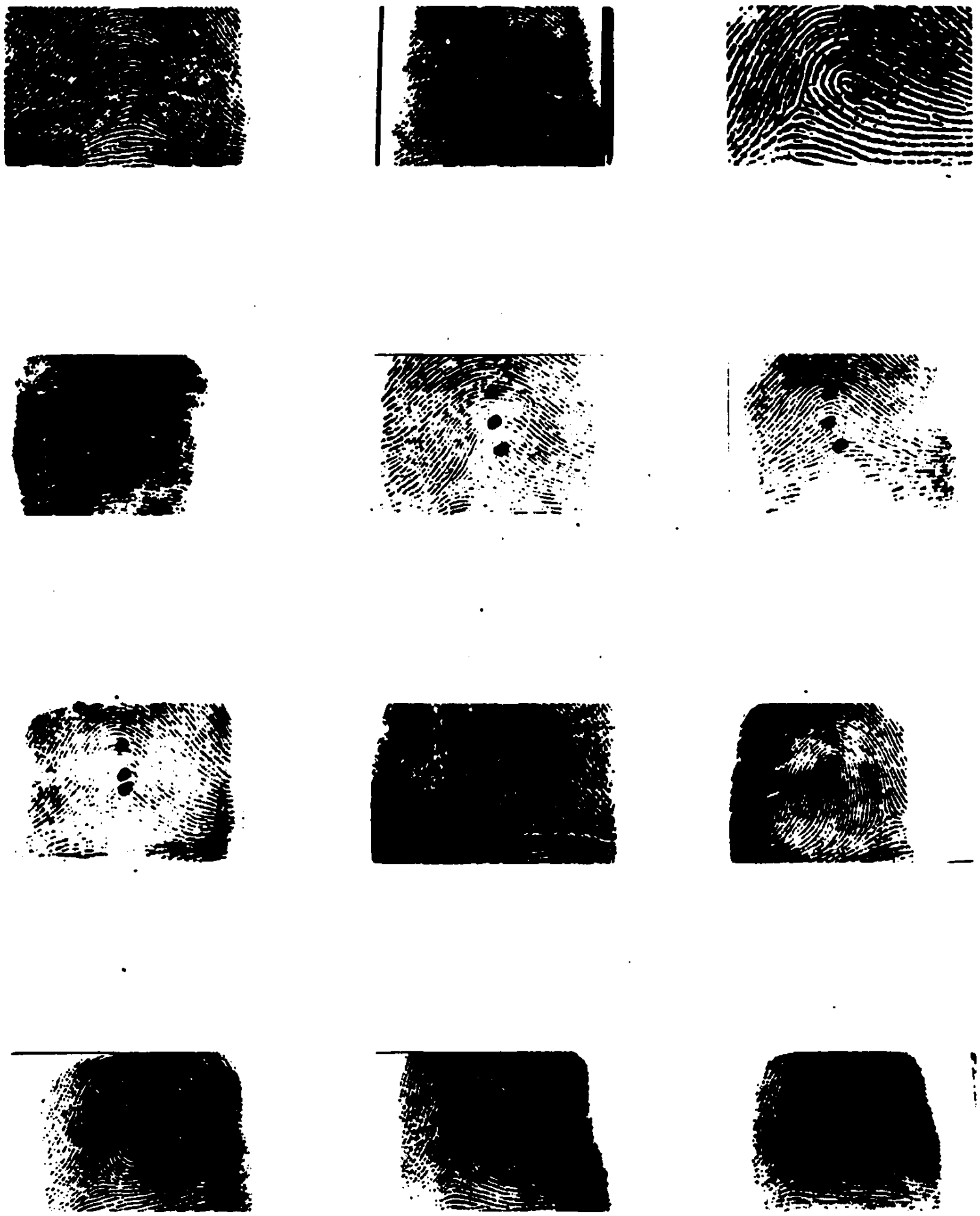


Plate 8

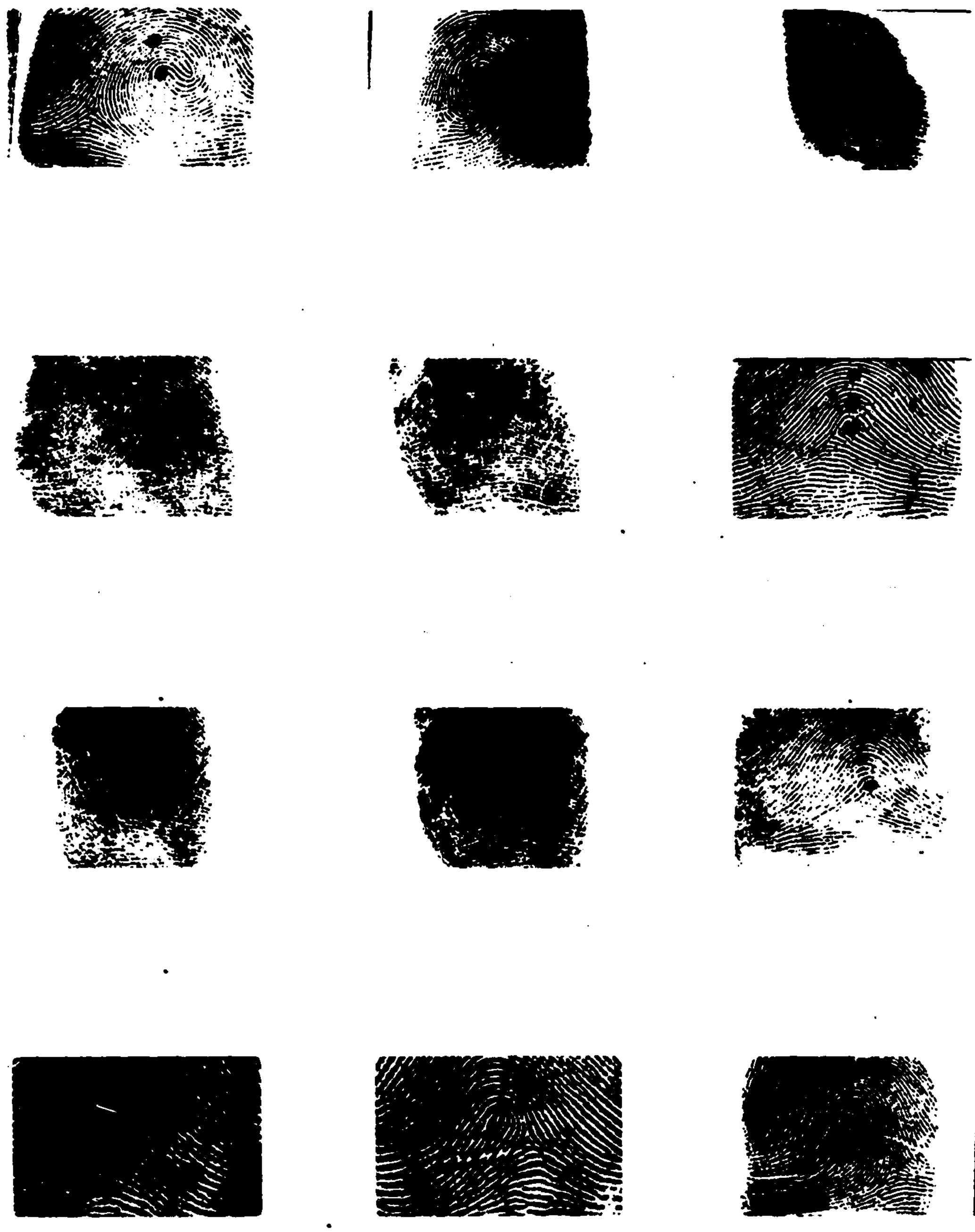


Plate 9

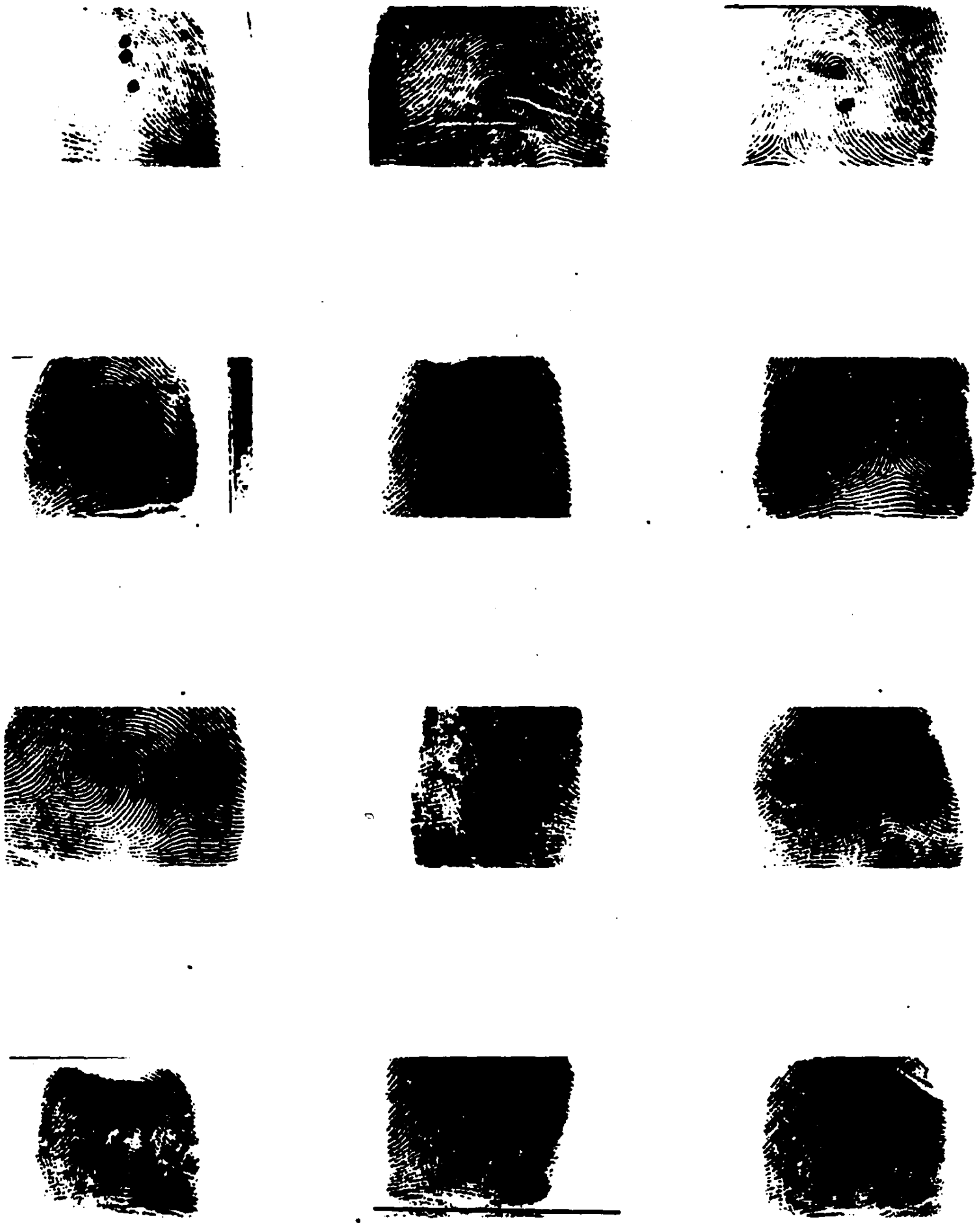


Plate 10

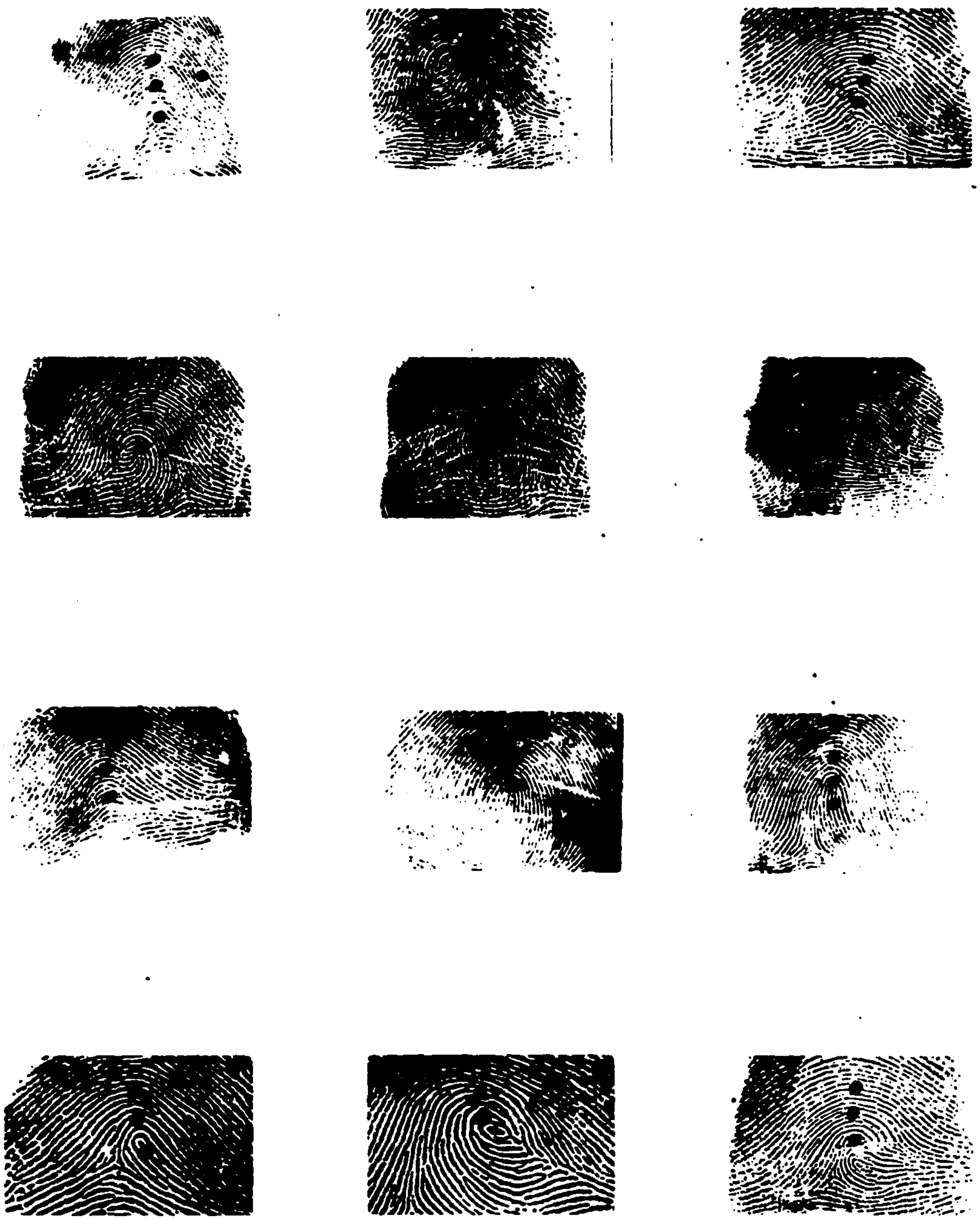


Plate 11

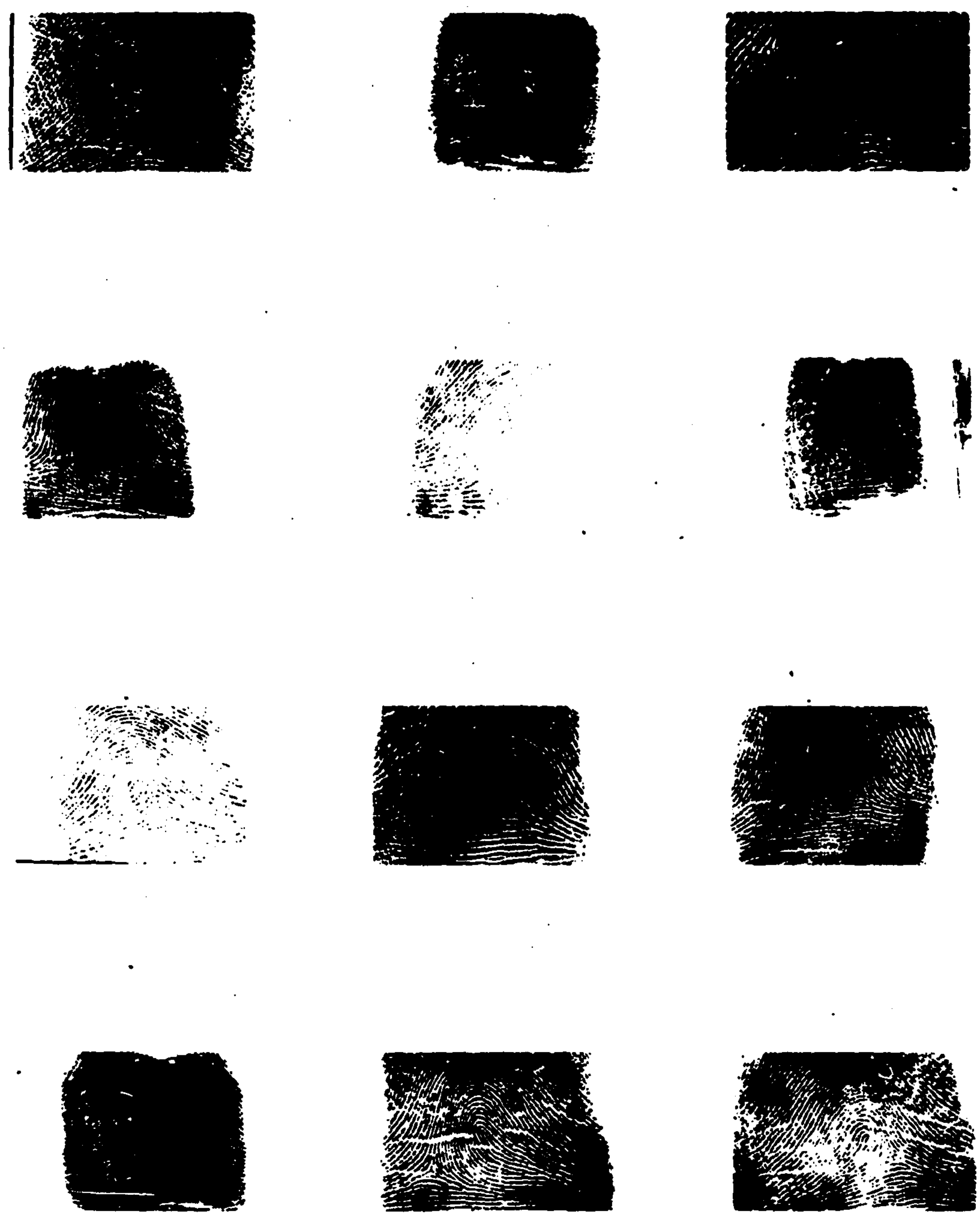


Plate 12

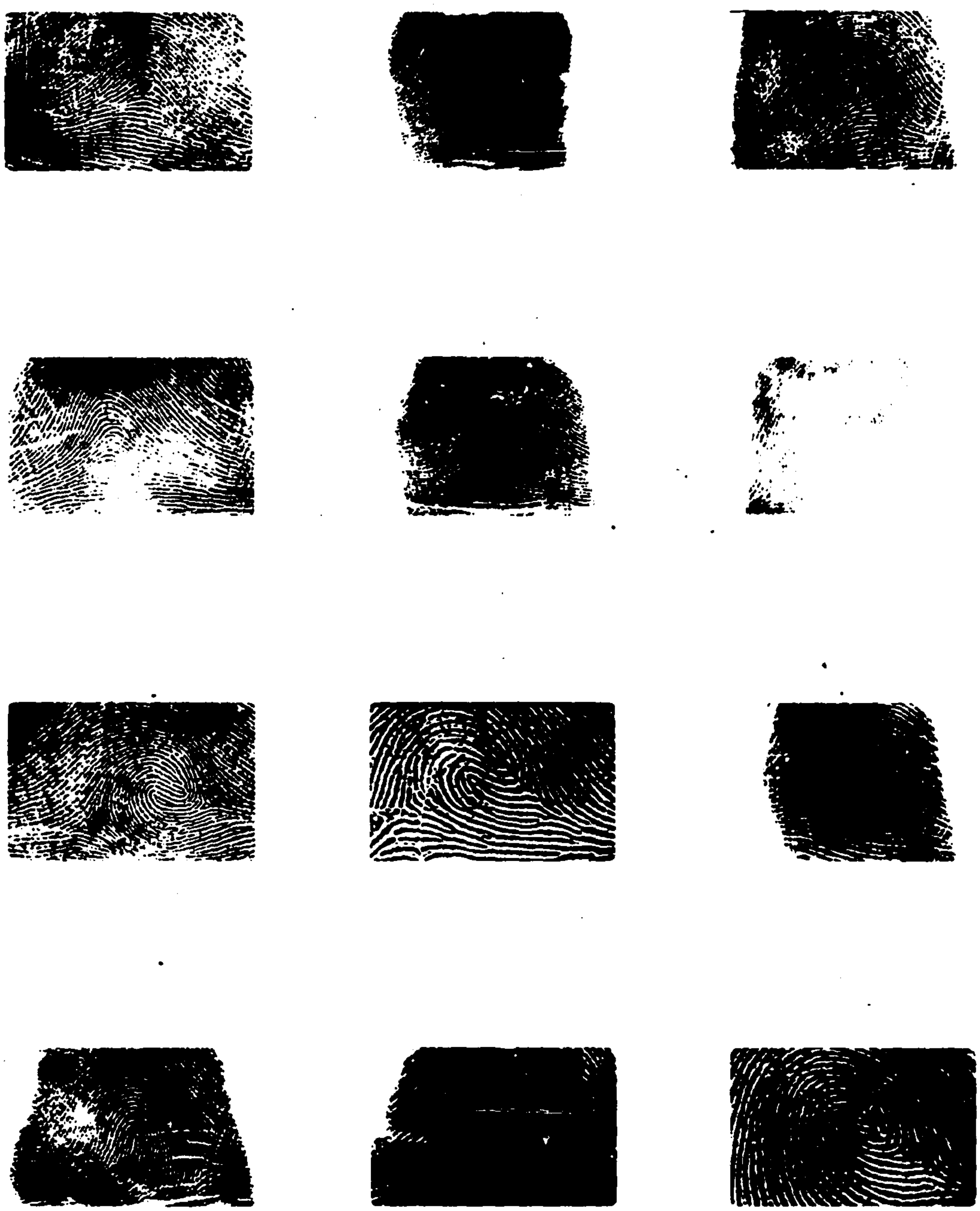


Plate 13

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