# A FUZZY IDS MODEL FOR IMAGE ENHANCEMENT

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May 1994

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Thesis Approved:

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# PREFACE

In this thesis we have examined the human retinal function and presented a fuzzy set theory based approach towards structuring a visual system. First, a visual system model based on the intensity dependent spread function (IDS) of the retina is discussed. Then it is combined with concepts from the fuzzy set theory to obtain a fuzzyfied model of a visual system. The application of this fuzzyfied model to different types of images simplifies several complex situations, *e.g.*, multiple occurrences of an object under different conditions, such as different amount of shading, contrast, *etc.* Another important issue is to quantify the improvement in enhancement. Two existing measures *viz.*, Error Root Mean Square (ERMS) and Bimodality analysis are discussed and a new performance evaluation method is suggested. Then the performance of the two visual system models is evaluated using the three methods. Evidently, the main advantage of using fuzzy set theory over the conventional probabilistic approach is found to be that it produces better quality results.

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# CHAPTER I

# INTRODUCTION

## Image Processing:

Image processing is being used for the processing of pictures returned from deep space, as an investigation tool for exploring Earth's resources, for Earth-based astronomy, for wealth predictions, for automated inspection, for robotics -- to the digitized T-shirts at the amusement park, and so on. With imaging and graphics becoming such an important aspect of our world, people from very diverse disciplines are working together for the first time. Electronics engineers, graphic artists, video technicians, layout artists, document processing professionals and computer programmers -- all are affected by the video revolution. All these advances have resulted in the emergence of a newer discipline -- *Image Processing.*

## Image Processing Subdivisions:

Image processing is concerned with the manipulation and analysis of pictures by computer [22]. When we "see" something, the light-sensitive cells behind the lens in our eyes capture a still image of the scene. Before we extract any information or associate some meaning to the contents of this image, it needs to be processed (*i.e.*, focussed, de-blurred, enhanced, *etc.*). Likewise, in an artificial visual system, we capture an image and process it in a similar fashion albeit digitally. Image processing is subdivided into the following three major areas:

a) Digitization and compression: Capturing analog (continuous) form pictures and converting them into digital (discrete) form; efficient coding or approximation of images so as to save storage space or channel capacity.

b) Enhancement, restoration and reconstruction: Improving degraded (blurry, noisy, low-contrast, etc.) images; reconstruction of images from sets of projections.

c) Matching, description, and recognition: Comparing and registering images to one another; segmenting images into parts, measuring properties of and relationships among these parts, and comparing the resulting descriptions to models defining the classes of images.

<u>Image Enhancement</u>:

In a complete system, such as the human eye, all of the above operations are carried out in the given sequence; it looks at an object, the focus and light controls are adjusted for better picture quality, image is captured, enhanced, then reconstructed from projections from both eyes. Then this image is matched with previously known facts and an attempt is made to associate a meaning with it.

However, in the world of science, efforts are still being made to construct such a system. Several subsystems have been developed by researchers to model and mimic different sub-systems. In the present study, we will focus only on the subsystem of *Image Enhancement.*

Different algorithms and techniques have been developed [25] for image enhancement and filtering based on various concepts from statistics, physics and other sciences such as sliding-windows, types of operations performed, and algorithmic implementation.

Fuzzy Set Theory:

Since Zadeh published his classic paper in 1965 [32], fuzzy set theory has been given more and more attention from researchers in a wide range of scientific areas, like decision-making models, control theory, are just to name a few.

The aim of this dissertation is to discuss the application of fuzzy set theory to the design and development of computational algorithms and processes and its use in developing a model of a part of the human visual system to enhance digital images. In the following chapter, we shall formalize the problem and define the scope of our work.

# CHAPTER II

# THE PROBLEM

## Introduction:

It is observed by several researchers that structuring the visual system is still a challenge [3, 16, 22]. The human visual system is very powerful and so far no artificial system has been designed to match it. Furthermore, the human visual system is very complex in nature and to this date it has escaped an accurate formalization. Therefore, the researchers use its properties or approximating models to improve image processing systems and then study the results to learn more about how people see [20]. Before proceeding any further, let us examine the human retinal function.

## Human Retinal Function:

When an image is to be enhanced so that at a later stage it can be interpreted by a human observer, the object of image processing, then, is to improve the subjective (visual) quality of the image as judged by that person. In simpler words, this is a process to match a given input image to the psychophysical properties of human visual perception. Psychophysical evidence has established that the human eye views an object by catching the light reflected from the surface of that object. If the effective flux density in an image is **I** (absorbed photons per unit time) per unit area, then both the mean and the variance of the actual quantum catch (actual number of photons absorbed in a single unit of time) during the same unit time over an area **A** equals **IA** [5].

Now, suppose that the light conditions change and the illumination changes from **I** to **I** + **ΔI** (where **ΔI** denotes a small change in the value of **I**). Then if we want to visually detect this change with an error rate of the order of **0.001**, the effect of the incident quanta must be summed over an area A to obtain the quantity **IA** large enough that $\mathbf{IA > 10/\Delta I^2}$. In other words, if the total number of quanta absorbed in the unit time are less than or equal to a certain quantity ( $\mathbf{10/\Delta^2}$ where Δ is the small change in the quantity ***I***), the human eye is unable to detect the change in light conditions.

Individual human photoreceptor collect these quanta over areas of the order of $\mathbf{10^{-5}\ mm^2}$ and perform the summation of their caught quanta over the temporal duration of the order of **0.1** sec. Therefore, below a certain light level, these photoreceptor cannot collect the required number of quanta and thus are unable to detect anything. We commonly refer to such light conditions as "dark."

<u>The IDS Principle:</u>

Spatial summation can thus be seen as pooling the retinal quantum catch over areas larger than a single receptor, allowing reliable contrast detection at scotopic and mesopic illumination levels. An important property of spatial summation is that the summation area becomes smaller as illuminance increases and the summation area increases with decreasing level of illuminance. This allows the human eye to perform better under various light conditions by keeping the quantity **IA** large enough to hold the inequality $\mathbf{IA > 10/\Delta^2}$. Intensity-dependent spatial summation has been formally described as:

> "Each point in the retinal image gives rise to a non-negative point-spread function whose height is directly proportional to image intensity at that point and whose volume remains constant -- so that the area covered by the point spread varies inversely with local image intensity. The output image is the sum of the point-spread functions generated around each input point." [5].

Different authors have implemented the IDS model using various statistical point spread functions. Most popular of these spread functions have been Gaussian function [2, 4, 5]. Other choices include cylindrical [2, 3], exponential [20], and conical functions [20].

A more detailed description of the IDS model and its assumptions will be presented in a later chapter.

Shortcomings of the IDS Model:

A common property of all these functions, and any other statistical point-spread function for that matter, is the way the summation is computed; all of which are defined over a fixed area and are integrated over the same area. This generates two problems:

a) These functions are defined over a continuous domain. However, for digital image processing the given input image is defined over a discrete domain. For instance, the digitized image is defined over the graytone levels { 0, 1, . . . , 255 }; whereas the IDS model is defined for all graytone levels in the closed interval [ 0, 255 ]. Consequently a lot of unnecessary computations have to be performed to compute the output image, which again is generated as a continuous image and is then mapped onto the discrete domain. Research is already in progress to develop a more applied IDS model suitable for discrete data [20].

b) These functions are defined over a fixed area regardless of the local illumination level. However, the IDS model requires these to be defined over a larger area in dimmer light conditions and smaller area under brighter conditions. This problem is solved by defining the point-spread function over a larger area and then after summation, the result is a threshold based on the local illumination level. This yields a lot of unnecessary computations that need not be computed if the spread function had taken into account the illumination level at the current pixel.

Therefore, the IDS model needs to be refined to resolve the above shortcomings.

Fuzzy Set Theory:

Fuzzy set theory was established by Zadeh [32] about thirty years ago and it has attracted more and more attention from researchers from a large spectrum of scientific areas. Its acceptance in Japan and the application to control problems has gained a wider audience especially in the past few years. It can be viewed as a powerful tool for modelling human reasoning. Humans have a remarkable ability to analyze very large amounts of data captured by their sensory organs and make rational decisions in an environment of uncertainty and imprecision.

The wide spectrum of applications of fuzzy set theory in general and its suitability to analyze human sensory data in particular has made it possible to be applied to several vision applications. Recent examples are the auto-focus cameras for still and video photography. The basic principle of these cameras is to adjust the focussing correctly using fuzzy set theory, to obtain a better picture in a short period of time. In a way, these cameras are the first attempt to model human vision.

In light of all this, we find the fuzzy set theory a very powerful tool to modify the IDS model.

In the following chapter, we present an overview of the work done on the IDS model so far along with some references to image processing in general as the necessary background. The last part of the literature overview shows some pointers to the fuzzy set theory.

# CHAPTER III

# LITERATURE REVIEW

## Image Enhancement:

Rosenfeld [23] has recently compiled a bibliography of nearly 1200 references related to computer vision, and image analysis arranged by subject matter. This survey paper shows the state of the art in computer vision and image analysis in 1991.

Rosenfeld and Kak [24] have also discussed different algorithms for digitization, compression, enhancement, restoration and reconstruction. This book also provides good mathematical background for image processing and visual perception.

V. T. Tom [28] has surveyed several adaptive techniques for image enhancement and filtering and has presented a taxonomy based on sliding-windows, types of operations performed, and algorithmic implementation.

Negrate *et. al.* [18] have developed a window-based contrast enhancement and noise filtering technique for graytone images. They have evaluated their technique using the bimodality analysis as a quality measure compared to human response needed in most existing techniques.

Aghagolzadeh and Ersoy [1] have discussed three blockwise transform image enhancement techniques, *viz.*, alpha-rooting, modified unsharp masking, and filtering modifications. They have compared the performance of these techniques to their own filtering technique motivated by the Human Visual System Response (HVSR), which also uses an overlap-save method to remove the block edge effects of the HVSR..

McCollum *et. al.*, [16] have designed an inexpensive hardware system for TV-rate high-speed image enhancement using the histogram modification technique based on the assumption that the statistical properties of images do not vary significantly from one TV frame period to another.

Tubbs [29] defined a family of image enhancement operators for context-free or context-sensitive enhancement that can be used either locally or globally.

The IDS Model:

The IDS model was presented by Cornsweet and Yellott in 1985 [5]. In their paper in the Journal of Optical Society of America, they described the theoretical background and assumptions of the model. They have also shown similarities between IDS processing and physiological properties of the retina also referred to as lateral inhibition.

A more elaborate discussion of the IDS is found in the Prentice Award Lecture by Cornsweet [4]. This lecture focusses more on how the IDS processing takes place and how does it react to different intensities and discusses the Weber's law and Ricco's law.

Applications of the IDS Model:

Alter-Gartenberg, Huck and Naryanaswamy [2] have shown that the reflectance recovery from the IDS bandpass data augments edge detection which can result in improved machine vision and image recovery.

Naryanaswamy, Alter-Gartenberg and Huck [2, 3, 16] have applied the IDS model to an image coding scheme which is robust to variations in illumination conditions, preserves high structural fidelity and also provides a high compression ratio.

Reese [22] has presented an adaptive, non-linear image enhancement method based on the IDS model. His method enhances edges, nonlinearly compresses the dynamic range and automatically adjusts to the local intensities in an image.

Fuzzy Set Theory:

Fuzzy set theory started with the seminal work of Zadeh in 1965 [32]. The rapid growth and popularity of the new field is shown by the fact that twelve years later Gains and Kohout [8] published a bibliography of 1150 articles related to different aspects of fuzzy set theory. In this paper, 750 citations were included to various applications of the fuzzy set theory including the introduction to fuzzy sets and its foundations, philosophy and logic of imprecision and vagueness, paradoxes, many-valued and other non-standard logic, fuzzyfication of mathematical systems. The remaining papers were about closely-related topics like linguistics, and psychology of vagueness.

Dubois and Prade [7] have written an excellent work on fuzzy set theory and the possibility theory, showing their relationship with and differences from the statistical probability theory.

Gupta *et al*., [10, 11, 14] have collected a set of papers showing the advances in fuzzy set theory and applications in its first two decades.

Klir and Folger [15] have written an excellent book on fuzzy sets, uncertainty, and information that can be used as a textbook for an introductory course on fuzzy set theory.

CHAPTER IV

# THE IDS MODEL

## Introduction:

The IDS model was presented by Cornsweet [4]. IDS stands for Intensity-Dependent Spread functions or Intensity-Dependent spatial Summation. This model shows how the cells in the retina interact with the brightness perception. The basic idea underlying the model is that given an input image, **I**, the retina produces an output image, **O**, using a spread function, S, such that every point in **I** contributes towards every point in **O**, subject to input intensity at each point in **I** and distance between **I** and **O**. The mathematical description of the model is as following [5]:

## Definition 1: Input image

The input image I is defined as a two dimensional Euclidean space (an x-y plane), where x and y are the two spatial variables. Let **I(x, y)** denotes the intensity of the input image at point **(x, y)**, where

$$I(x, y) \geq 0 \qquad \text{for all x and y}$$

Definition 2: Output image:

The output image **O** is defined as another two dimensional Euclidean space (p-q plane), where **p** and **q** are the two spatial variables. Then **O[I(x, y)] (p, q)** denotes the output image intensity at point **(p, q)** when input image is **I(x, y)**. When the input image is obvious, we simply use **O(p, q)** for the output image.

Definition 3: Spread function:

The spread function **S** has the general form **S {(x, y), (p, q), I)}**, and it defines the relationship between the input image, **I**, and the output image, **O**, such that every point in **I** contributes a non-negative point-spread value to every point in **O**. The amount of this contribution depends on the input intensity at **I(x, y)** and the distance from **(x, y)** to **(p, q)**. The spread function, **S**, satisfies the following necessary and sufficient conditions [5]:

i) **S is non-negative:**

This condition implies that the intensity level of any pixel in the given input image can only make either no contribution towards the enhancement of its neighbors or it makes a positive contribution.

ii) **S is spatially homogeneous and circularly symmetric:**

In other words, **S** can be expressed as a function of two real variables in the form

$$S\{[(x - p)^2 + (y - q)^2],\ I\} \quad = \quad I(x, y) \times S\{I(x, y) \times [(x - p)^2 + (y - q)^2]\}$$

This property emphasizes the fact that when we are enhancing a pixel X in the given input image, any two pixels $(a_1, b_1)$ and $(a_2, b_2)$ at an equal distance from **(x, y)** have an equal chance to make a contribution towards the enhancement of the pixel **(x, y)**.

iii) **The integral of $S\{[(x - p)^2 + (y - q)^2], I\}$ over the p-q plane equals 1.0:**

Since the spread function is a probability function defining the probable contribution of each neighboring pixel towards the enhancement of a given pixel, the sum of all these probabilities must be 1.0.

iv) **No height of the spread function is greater than that at its center point (p, q) and this height is proportional to I(p, q), the intensity at that center point:**

This property underlines the fact that the original intensity level of a pixel X in the input image plays the biggest role in computing the enhanced intensity value for that pixel. No other pixel makes as much contribution towards the new value as the pixel X itself.

Different statistical spread functions, like Gaussian, exponential, cylinder and cone have been used in the literature in image processing applications [2, 3, 4, 5, 20]. Some of these spread functions (*e.g.*, cylinder and cone) are non-zero only for a finite distance from their center (radius of support), while some others (*e.g.*, Gaussian and exponential) extend over the entire plane. The region for which a spread function is non-zero is called its *region of support*.

The output from IDS at some point **(x, y)** is defined as:

$$\mathbf{O(x, y)} \quad = \quad \int_0^N\int_0^M \mathbf{I(p, q)\ S\ \{I(p, q)\ [(x - p)^2 + (y - q)^2]\}\ dp\ dq}$$

where $\mathbf{0 \preceq p \preceq M}$ and $\mathbf{0 \preceq q \preceq N}$. This is also referred to as the fundamental equation of IDS. When we want to enhance an image or remove the noise from it, we compute the IDS output of the entire image. This forms a filter image. Then the enhanced image is obtained by adding the IDS image to the original image.

Symbolically,

$$\mathbf{E(x, y)} \quad = \quad \mathbf{I(x, y) \vee O(x, y)}$$

In the following chapter, we shall present an overview of fuzzy set theory and its important properties and applications.

# CHAPTER V

# AN OVERVIEW OF FUZZY SET THEORY

## Introduction:

A fuzzy number can be considered as an extension to the concept of an *interval of confidence* [13]. This extension enables us to consider the confidence interval at several levels at the same time, and more generally at all levels in the range **0** to **1**. Then the maximum of presumption is at **1** and the minimum level of presumption is at **0**. Also, the level of presumption $\mu$, $\mu \in [0, 1]$ gives an interval of confidence $A_\mu=[A_1^{(\mu)}, A_2^{(\mu)}]$, which is a monotonically decreasing function of $\mu$; that is,

$$(\mu' > \mu) \Rightarrow (A_{\mu'} \subset A_\mu)$$

$$\text{or} \quad (\mu' > \mu) \Rightarrow ([A_1^{(\mu')}, A_2^{(\mu')}] \subset ([A_1^{(\mu)}, A_2^{(\mu)}] \qquad \forall\, \mu, \mu' \in [0,1]$$

Let us assume, for example, that a certain job is to be completed between two dates, say February 21 and February 28. This is an interval of confidence [February 21, February 28] and can also be represented as **[0, 1]**. Note that the underlying concept is independent of the interval size, that is

$$\mu_1 < \mu_2 \Rightarrow [A_1^{(\mu_1)}, A_2^{(\mu_1)}] \subset [A_1^{(\mu_2)}, A_2^{(\mu_2)}] \qquad \forall\, \mu_1, \mu_2 \in [0,1]$$

This means that if $\mu$ increases, the interval of confidence never widens [13].

Here, if we define **X** as a set in the classical sense, that is as a characteristic function $\mu_A$ from **X** to **{0, 1}**, such that

$$\mu_A(x) = \begin{cases} 1 & \text{iff} \quad x \in A \\ 0 & \text{iff} \quad x \notin A \end{cases}$$

Then, a fuzzy set is a generalized subset of a classical set **X** with $\mu_A(x) \, \varepsilon \, [0,1]$ being the grade membership of an element in the set **A**. Formally, a fuzzy set A with its finite numbers of supports $X=\{x_1,x_2,\ldots,x_n\}$ is defined as a collection of ordered pairs

$$A = (\mu_A(x_i), x_i) \qquad i = 1, 2, \ldots, n$$

Clearly, **A** is a subset of **X** that has no sharp boundary [10]. Using this principle, other concepts from the classical set theory have been adopted into the fuzzy logic. These fuzzyfied concepts include:

| | | | |
|---|---|---|---|
| union | intersection | | complement |
| support | normalization | and | empty set |

Properties of a Fuzzy Set:

The following properties have been associated with the above fuzzy set operations:

**a)** **commutativity:**

$$A \cup B = B \cup A \quad ; \quad A \cap B = B \cap A$$

**b)** **associativity:**

$$A \cup (B \cup C) = (A \cup B) \cup C$$

$$A \cap (B \cap C) = (A \cap B) \cap C$$

c) **idempotency:**

$$A \cup A = A \quad ; \quad A \cap A = A$$

d) **distributivity:**

$$A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$$

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

e) **identity:**

$$A \cup \phi = A \quad ; \quad A \cup X = X$$

$$A \cap \phi = \phi \quad ; \quad A \cap X = A$$

f) **absorption:**

$$A \cup (A \cap B) = A \quad ; \quad A \cap (A \cup B) = A$$

g) **complement:**

$$\bar{A} = (1 - \mu_A(x)) / x$$

h) **involution:**

$$\bar{\bar{A}} = A$$

i) **De Morgan's laws:**

$$\overline{(A \cup B)} = \overline{A} \cap \overline{B} \quad ; \quad \overline{(A \cap B)} = \overline{A} \cup \overline{B}$$

j) **equivalence formula:**

$$(\overline{A} \cup \overline{B}) \cap (A \cup B) = (\overline{A} \cap B) \cup (\overline{A} \cap B)$$

k) **symmetrical difference formula:**

$$(\overline{A} \cap B) \cup (\overline{A} \cap B) = (A \cup B) \cap (\overline{A} \cup \overline{B})$$

l) **boundedness:**

A fuzzy set **A** is said to be bounded if and only if for all $\alpha > 0$, the corresponding sets $A_\alpha = \{ x \mid f_A(x) \geq \alpha \}$ are bounded.

The only law of ordinary set theory that does not hold for fuzzy sets is the excluded-middle law:

$$A \cap \bar{A} \neq \phi \quad ; \quad A \cup \bar{A} \neq X$$

Since the fuzzy set **A** has no definite boundary and neither has $\bar{\mathbf{A}}$, it may seem only natural that **A** and $\bar{\mathbf{A}}$ overlap, which is always limited as

$$\min\left(\mu_A(x),\ \mu_{\bar{A}}(x)\right) \leq 1/2 \qquad \forall A,\ \forall x$$

For the same reason, $\mathbf{A} \cup \bar{\mathbf{A}}$ do not exactly cover **X**; however,

$$\min\left(\mu_A(x),\ \mu_{\bar{A}}(x)\right) \geq 1/2 \qquad \forall A,\ \forall x$$

Even though every operation that can be carried out using ordinary numbers can also be carried with fuzzy numbers, many properties change as we pass from one family to the other. Although this is important, it should not prevent us from using the concepts and theory of fuzzy numbers. The world of perception does not have sharp edges. It is full of ambiguity and uncertainty, and it is only reasonable to make use of the fuzzy set theory.

Applications of Fuzzy Set Theory:

Fuzzy sets allow information to be approximately summarized in a human-like fashion. It provides the right tool for approximate reasoning or for a generalized tolerance analysis. From this point of view the specification of a fuzzy system consists in a linguistic description of its behavior and/or assignment of fuzzy parameters to an ordinary mathematical model. Fuzziness may lie in the system itself or in its model. It is mainly a matter of human perception.

A great amount of work has already been accomplished. So far, fuzzy set theory has largely been applied to scientific areas where man is somewhat involved. However, there are some exceptions like the detection of hazards in switching circuits, functional approximation and quantum mechanics [10]. The following is a brief listing of some of these achievements in *fuzzyfication*:

a) Computer Science

b) Biological and Medical Sciences

c) Control Theory

d) Economics

e) Sociology

f) Engineering

In the next chapter, we shall explain how fuzzy set theory can be applied to construct spread functions and subsequently the fuzzy IDS model.

# CHAPTER VI

# THE FUZZY IDS MODEL

## Fuzzy Spread Function:

The IDS model enhances the image by creating bands at steps in intensities and the peak amplitude of the IDS output depends only on the ratio of intensities of two adjacent bands. This property enables the structure not only to enhance the contrast but also enhances the edges at the same time.

We observe that the intensity level is constant in one band, changes as soon as we cross into the adjacent band and then remains constant in that band. We can consider this crossover as a "*linguistic hedge*" as defined by Zadeh [29]. Then we have "*low intensity*" on one side of this hedge and "*high intensity*" on the other side of this hedge. Then, we can consider each of these intensity levels as fuzzy subsets containing pixels of the same intensity [23]. Subsequently, we can consider the x-y plane as a fuzzy set with each point **I(x, y)** in the given image having a non-negative membership in this plane. Zadeh has defined the membership function of a fuzzy set as [29]:

$$
\begin{aligned}
S(x; a, b, c) &= 0 && x \le a \\
&= 2\{(x - a) / (c - a)\}^2 && a \le x \le b \\
&= 1 - 2\{(x - a) / (c - a)\}^2 && b \le x \le c \\
&= 1 && x \ge c
\end{aligned}
$$

with $b = (a + c) / 2$

Here, **b** is the crossover point which separates two adjacent intensity bands in the given image. The symbol **S** is used here because of the shape of this spread function as shown in Fig. 1. This is a very simple spread function compared to most statistical spread functions in use. However, it does not satisfy the second condition of the spread function, *i.e.*, it is not circularly symmetric.

We can overcome this problem by combining two **S** functions back to back to yield a more familiar looking bell-shaped spread function (see Fig. 2). We can further simplify this spread function by substituting **c = 0** and **b = 1** and rotating it about the z-axis, so that:

$$r = \sqrt{x^2 + y^2}$$

so that

$$
\begin{aligned}
F(x, y) &= 0 && \text{for } r > 1 \\
&= 2(1 - r)^2 && \text{for } ½ \le r \le 1 \\
&= 1 - 2r^2 && \text{for } 0 \le r \le ½
\end{aligned}
$$

Here, F is a fuzzy membership function as it maps the intensities of pixels into the interval [0, 1]. We call **F** a fuzzy spread function if it satisfies all the conditions of a spread function.

Conditions for a Fuzzy Spread Function:

We call **F** a fuzzy spread function if it satisfies the following conditions which are necessary and sufficient for a spread function in the IDS model.

a. F is non-negative:

By definition,

$$\mathbf{F(x, y) \geq 0 \qquad \text{for all } x, y}$$

b. F is peaked around the center:

**F (x, y)** is maximum when **x = 0** and **y = 0** and the maximum value is **1**. Therefore, the highest point of the fuzzy spread function, **F**, is its center point **x = y = 0** and this height is proportional to **I(p, q)**, the intensity at that center point.

c. F is spatially homogeneous and circularly symmetric:

If $\mathbf{r \geq 1/2}$ then

$$\begin{aligned} \mathbf{F(-x, -y)} &= \mathbf{2\{1 - [(-x)^2 + (-y)^2]^{1/2}\}^2} \\ &= \mathbf{2\{1 - [(x)^2 + (y)^2]^{1/2}\}^2} \\ &= \mathbf{F(x, y)} \end{aligned}$$

and if $\mathbf{r \leq 1/2}$ then

$$\begin{aligned} \mathbf{F(-x, -y)} &= \mathbf{1 - 2[(-x)^2 + (-y)^2]^{1/2}} \\ &= \mathbf{1 - 2[(x)^2 + (y)^2]^{1/2}} \\ &= \mathbf{F(x, y)} \end{aligned}$$

Thus, **F** can be expressed in the form

$$\mathbf{F}\ \{[(\mathbf{x} - \mathbf{p})^2 + (\mathbf{y} - \mathbf{q})^2],\ \mathbf{I}\}$$

implying that **F** is spatially homogeneous and circularly symmetric.

d. The volume of **F** is **1**:

We have already established the input image as a union of singleton fuzzy sets with each pixel representing its membership in the universal fuzzy graytone set. In other words, the intensity of illumination of a pixel is represented by its degree of membership in the contributing set.

The fuzzy integral (also called the *Sugeno's integra*l [30]) of a fuzzy function, **F**, with respect to its membership function, $\mu$, is defined for a set **A** as:

$$\int_A F\,d\mu \;=\; sup_{\alpha\in[0,\infty]}\ [\alpha \wedge \mu(A \cap F_\alpha)]$$

| | | | |
|---|---|---|---|
| Here, | **A** | = | The universal set [0, 255] |
| and | $\mathbf{F}_\alpha$ | = | alpha-cut of a unimodal continuous function **F** such that all $\mu \geq \alpha$, where $0 \leq \alpha \leq 1$. |

Now, we have $0 \leq \alpha \leq 1$; $0 \leq \mu \leq 1$; and $\mu \geq \alpha$. Since the maximum value of **F** is **1** (see part *b* above), that would also be the value of the fuzzy integral.

Therefore, we see that the fuzzy spread function fulfills all the assumptions for an IDS spread function.

## CHAPTER VII

## IMPLEMENTATION ISSUES

Introduction:

Computer science has its historical foundations in mathematics. Computing algorithms are developed using mathematical techniques. The performance of these algorithms is also evaluated using some mathematical techniques. However, most of these techniques and models have been evolved from continuous distributions and series. Whereas, present day computers are digital and hence are governed by discrete laws. Therefore, several issues need to be resolved when an algorithm is developed in a continuous domain and is then ported into a discrete domain.

In this chapter we will discuss various issues and problems encountered while designing and implementing the two IDS models and how they have been resolved.

Window size:

Given an input image of **200** rows with **200** pixels in each row, the conventional IDS model assumes that each pixel in the input image has some non-negative contribution towards every pixel in the enhanced image, and therefore, has to be computed for each pixel in the input image and then summed to produce one pixel

in the output image. Therefore, **200 x 200** computations to calculate one pixel in the output enhanced image. Now, if the output image is to be produced in the same size as the input image, the total number of
computations will be:

$$(200 \times 200) \times (200 \times 200) = (200)^4$$

$$= 1.6 \times 10^9$$

However, for practical purposes a sliding window is used. The most commonly used spread function is Gaussian function which includes 95% points in the interval:

**[mean + standard deviation, mean - standard deviation]**

Window edges:

The above approach works fine for most of the pixels in the input image. However, for the pixels on the extreme sides and corners, the enhancement window does not have enough pixels to correctly evaluate the spread function. Therefore, an approximate and inaccurate result is produced for such pixels.

For our implementation we have chosen to ignore the very extreme pixels in the input image and their value is simply copied into the enhanced image. For a fair evaluation, this is done for both implementations of the conventional IDS and the fuzzyfied IDS model. The result is that in the enhanced image there is an extra edge on all four sides which is one pixel wide. On some images this edge is more visible than others.

Test images:

Eleven test images were used for evaluation of our implementations. These images are frequently used in the image processing literature and present a fine blend of different combinations of pixel intensities.

All the images used for our purposes are 200 x 200 pixels and have 256 graytone levels. This choice was made so that the 320x200x256 VGA mode could be used.

Test image format:

The test images were obtained in different formats and sizes. For uniformity purposes they were all rescaled to 200 x 200 size. Also, they were all converted to Compuserve Graphical Information Format (GIF) 1987 non-interlaced format.

Hardware:

The computing machine used for this work was an IBM PC clone with the following configuration:

- Cyrix 486-DLC/40 CPU
- 1 K Bytes internal cache
- 128 K Bytes external cache
- 4 Mega Bytes RAM with average access time = 60 nano sec
- Trident VGA card using VGA mode 13h = 320 x 200 x 256
- Viewsonic 6 super VGA monitor

Software:

The implementation, testing and evaluation programs were developed using the following tools:

- MS-DOS ver 6.2
- Borland Turbo C 2.01

Having resolved all the above issues, we got ourselves a fair and standardized environment to test and compare both the conventional IDS model and the fuzzyfied IDS model.

In the following chapter we present some performance evaluation techniques that we used to evaluate and compare our algorithms.

# CHAPTER VIII

# EVALUATION TECHNIQUES

## Introduction:

A very important part of algorithm development is its implementation and testing. When the sole purpose of the algorithm is to improve or enhance the quality of an image, a need arises for evaluating its performance and comparing it with similar algorithms.

## Visual inspection:

Images are used to present some information. When after applying an algorithm, an image presents more information or is more appealing we say that its quality has improved. In other words, the ultimate goal of image processing is to make an image more useful for its human users. Therefore, human visual inspection is a good test of performance.

We have presented the eleven test images in the Appendix II as following:

| | |
|---|---|
| Appendix II-1-a through II-11-a | Original images |
| Appendix II-1-b through II-11-b | Conventional IDS enhanced images |
| Appendix II-1-c through II-11-c | Fuzzyfied IDS enhanced images |

Histogram analysis:

Histogram analysis is a very popular technique in the image processing literature [18]. Here, an image is converted into a frequency histogram where the x-axis shows the graytone levels and the y-axis shows the number of pixels for each level. An histogram represents a higher contrast if the values are pulled towards the two far extremes *i. e.*, bright white and the dark black levels. A more evenly distributed histogram shows a less sharper image.

We have presented the eleven test images in the histogram format in the Appendix III as following:

| | |
|---|---|
| Appendix III-1-a through III-11-a | Original images |
| Appendix III-1-b through III-11-b | Conventional IDS enhanced images |
| Appendix III-1-c through III-11-c | Fuzzyfied IDS enhanced images |

Error Root Mean Square (ERMS) Analysis:

Statisticians use this technique to quantify the deviation of a given pattern from a standard pattern. Here, we can use this technique to find the difference between the original image $\boldsymbol{O}_i$ and the enhanced image $\boldsymbol{E}_i$. We compute the sum of the squares of the difference between the corresponding pixels in both images. The resulting number is divided by the square of the size of the image $\boldsymbol{N}$ (both images are of the same size). The resulting value is called ERMS.

$$ERMS\ (O,E) = \sqrt{\frac{\sum (O_i - E_i)^2}{N^2}}$$

We can evaluate the performance of an algorithm by this quantity, ERMS. A higher ERMS indicates more change and therefore, more enhancement for our purpose. On the other hand, a lower ERMS means smaller change and thus indicates less improvement for us.

The ERMS values are shown in numerical form in Appendix IV-a and in graphical form in Appendix IV-b.

Since our purpose is to evaluate the performance of two different methods, we have also computed the average ERMS of all eleven images, shown at the bottom row in Appendix IV-a and the last bars in the histogram in Appendix IV-b.

Bimodality Analysis:

One way of defining the contrast is the differentiation between two levels of graytone. Phillips *et. al.*, as quoted in [18] stated that a good way to evaluate the separability of such classes is to use bimodality analysis. They defined the bimode for a population $\boldsymbol{P}$ as the Fisher distance between the two classes $\boldsymbol{P_1}$ and $\boldsymbol{P_2}$ of $\boldsymbol{P}$, where Fisher distance is defined as:

$$FD(t) = \sqrt{\frac{\alpha(\mu_1 - \mu_2)^2}{(\alpha_1 \sigma_1^2 + \alpha_2 \sigma_2^2)}}$$

| | | |
|---|---|---|
| where | $t$ | graytone threshold that separates the two classes |
| | $\alpha, \alpha_1, \alpha_2$ | respective sizes for P, $P_1$, and $P_2$ |
| | $\mu, \mu_1, \mu_2$ | respective means for P, $P_1$, and $P_2$ |
| | $\sigma, \sigma_1, \sigma_2$ | respective standard deviations for P, $P_1$, and $P_2$ |

Obviously, a larger bimode value at a graytone level $t$ indicates a high contrast ratio between pixel intensities more than $t$ and those less than $t$.

Now, it follows from the above discussion that a bimode is defined for each level of graytone. Since each of the images used in our research has 256 graytone levels, we have computed 256 bimodes for each image. Also, these bimodes were computed for each enhanced image obtained using the conventional IDS model as well as the fuzzyfied IDS model. The plots of these bimodes for each of the eleven test images are shown in the Appendices V-1 through V-11.

Average Bimodality Analysis:

The previous method presents a total of 256 values for each original image, conventionally enhanced image and the fuzzyfied enhanced image. These are a large numbers to really quantify the change in the quality of an image.

One way of simplifying the issue is to compute an average of all the bimodes computed for an image. Thus we will have only three numbers, one for each original image, conventionally enhanced image and the fuzzyfied enhanced image. These average bimodes are shown in tabular form in Appendix VI-a and in the graphical form in Appendix VI-b.

Again, our purpose being the evaluation of the performance of two different methods, we have also computed an average of all of the average of all eleven images, shown at the bottom row in Appendix VI-a and the last bars in the histogram in Appendix VI-b.

ERMS analysis of Bimodes:

A major disadvantage of using an average to represent a set of values is that if one of these values is large or small enough, it can skew the whole representation. Therefore, it may be wiser to compute the square of the differences between bimodes of the original image and the enhanced image. Then we can obtain a single value by dividing the square root of the sum of these squares by the square of the population size, *i.e.*, the number of the bimodes used in the research. In simpler words, we can represent a set of bimodes more accurately by its ERMS value. In this way we can control the effect of a single graytone level versus a set of these levels.

These ERMS'ed bimodes are shown in tabular form in Appendix VII-a and in the graphical form in Appendix VII-b.

Also, we did compute an average of all of the ERMS bimodes of all eleven images used in our research. These global averages are shown at the bottom row in Appendix VII-a and the last bars in the histogram given in Appendix VII-b.

In the above discussion, we have shown some existing as well as new evaluation methods and presenting their results in numerical and graphical form. We are now ready to proceed to the next chapter to discuss our findings and to draw some conclusions from them.

# CHAPTER IX

# FINDINGS AND CONCLUSIONS

## Introduction:

Image contrast enhancement is a very delicate process. The original data are obtained from one medium of input and is targeted at another medium. In our case the input data are obtained from analogue camera and scanner and is targeted to be digitally displayed on the monitor of a PC. Our goal is to display these images so that they show maximum information while loosing minimum resolution. However, when continuous analog information is digitized, a certain loss occurs in the process of approximating discrete gray levels from continuous graytone.

Also, while enhancing the contrast in an image, we are effectively substituting the gray level of a pixel with a lighter or darker level to increase its visibility amongst its neighbors. We can stretch this process to an extreme by substituting only black or white pixels and thus obtaining a very sharp two-level image. However, we will lose other details in the image, thus making the enhanced image less useful.

Therefore, we must choose an algorithm which performs these substitutions while losing as little detail as possible.

In our research we have used an image contrast enhancement technique which models the human visual system, particularly the retinal function. This technique was developed using the boolean logic of black and white values. In real life, however, we deal with objects that are somewhat black, gray or white. Therefore, we extended the IDS principle using concepts of fuzzy logic and thus obtained a fuzzyfied IDS model.

The next question was comparing the performance of these two models. Traditionally, an image is considered as a qualitative object and its quality is measured visually or by associating an average as a quantity. The problem in these cases is that an average provides a very biased representative. Simply put, if all the pixels in the image are uniformally distributed over the entire the graytone scale, an average is fine. But as the case is most of the time, some shades of gray occur more frequently in an image than others. Keeping this we also proposed a quantitative measure as a new metric to represent the quality of an image and help us determine more accurately the change in its quality.

Now let us examine these two IDS models using these evaluation techniques.

Visual inspection:

The eleven test images used in our research are shown in Appendix II in three different forms:

i. their original form

ii. enhanced using the conventional IDS model

iii. enhanced using the fuzzyfied model

We note the following observations about these images:

a. The quality of the image on the VGA screen is different as we have 256 graytone levels available to display the image. However, on paper we do not have such wide band of gray so we lose quality when printing on paper.

b. The quality of the original images was fairly good while the improvements using the two enhancement methods were very close at certain levels.

c. The overall quality of each of these images is improved. However, generally, there is no dramatic change in these images since both enhancement methods treat input image very delicately, trying to preserve as much detail as possible.

d. Quality of an image is a human judgmental issue. One image may be preferred by one human while another one may be liked by some one else.

Histogram analysis:

The histograms for the eleven test images as well as the conventional IDS enhanced images and the fuzzyfied IDS enhanced images are shown in the Appendix III. We notice that the IDS enhancement process tries to redistribute the pixels among the graytone levels, making the resulting histogram more flat with lesser peaks. Also, our fuzzyfied method performs better by stretching this redistribution towards the extremes of the gray scale, producing a flatter histogram.

Error Root Mean Square (ERMS) Analysis:

We evaluate the performance of an algorithm using ERMS such that a higher ERMS indicates more change and therefore, more enhancement in our case. On the other hand, a lower ERMS means smaller change and thus less improvement for us.

The ERMS values are shown in numerical form in Appendix IV-a and in graphical form in Appendix IV-b.

We notice that the ERMS values for fuzzyfied IDS are higher than their conventional IDS counterparts. This change does depend on the redistribution of pixels over the gray scale as well as the effect of the neighboring pixels over the change in each pixel.

Since our purpose is to evaluate the performance of two different methods, we have also computed the average ERMS of all eleven images, shown at the bottom row in Appendix IV-a and the last bars in the histogram in Appendix IV-b. We notice that this value is 3.346 for the change from original to conventionally enhancement, while 3.354 for the change from the original to fuzzyfied enhancement, showing a slight improvement over the conventional IDS enhancement.

Bimodality Analysis:

Conceptually, a bimode for a particular gray level represents an average distance between pixels darker than that level and those lighter than it. This average is biased by the number of pixels in each of these two classes and their average deviation from the mean of each class. We have computed 256 bimodes for each original image as well as each enhanced image obtained using the conventional IDS model and the fuzzyfied IDS model. The plots of these bimodes for each of the eleven test images are shown in the Appendix V.

We observe the plot of the fuzzyfied IDS bimodal curve higher than the conventional IDS bimodal curve. Also, generally the distance between the fuzzyfied IDS bimodal curve and the original image bimodal curve is wider than that of the conventional IDS bimodal curve and the original image bimodal curve.

Average Bimodality Analysis:

The simple bimodality analysis presents a total of 256 values for each original image, conventionally enhanced image and the fuzzyfied enhanced image. This is a rather large set of quantities to measure the change in the quality of an image. To make the evaluation of the performance of two different methods more practical, we computed an average of all of these bimodes for each image as well as a grand average of all eleven images, shown in both numerical and graphical form in Appendix VI.

We observe our fuzzyfied model's values to be higher than those for the conventional IDS model. We find the grand average as 5.28 for the original images, enhanced to 5.40 using the conventional IDS method. This quantity reached an impressive 5.92 when the fuzzyfied technique was used.

ERMS analysis of Bimodes:

This is our new evaluation method in which we use a quantity obtained by performing an ERMS on the bimodes computed for graytone levels in our test images. We find that this single quantity shows an average change in the quality of an image.

However, this quantity is not skewed by an uneven distribution of pixels over the graytone scale. Also, this quantity reflects the redistribution in the pixel neighborhood since corresponding differences in pixel bimode values are squared and then averaged over the entire scale.

Examining these values in numerical and graphical form in the Appendix VII, we find our fuzzyfied method showing an average gain of 31.25% in enhancement quality improvement of 210 x $10^{-6}$ over the average value of 160 x $10^{-6}$ obtained using the conventional method. Our method also shows various levels of improvement over various images, ranging from 50 x $10^{-6}$ to 786 x $10^{-6}$ compared to conventional IDS enhancements ranging form 40 x $10^{-6}$ to 437 x $10^{-6}$; thus indicating a better redistribution of pixels in the image to improve contrast enhancement.

Special Cases:

In the previous cases, we have examined and enhanced images in their original form as they wer obtained. Repeating the same image enhancement procedures for images that were deteriorated prior to enhancement resulted in similar way. Appendix VIII shows an image that was obtained in 256 greytone levels. It was then reduced to 16 greytone levels and then it was enhanced using the conventional IDS method as well as the fuzzy IDS enhancement. We observed that as a result of reducing the greytone levels, the pixels were clustered into 16 groups. The enhancement attempts to improve the image by spreading the pixels. This de-clustering is obversed to be more effective, as seen in Appendix VIII.

In a similar way, an image was obtained in good shape and was then smoothed using a Gaussian filter. The result was clusterng all pixels towards the lighter greytone level, thus reducing the sharpness in the image. Then we enhanced the image using the conventional IDS method and the fuzzy IDS method. We observed that the enhancement process redistributes the pixels in an effort to pull the cluster towards the darker greytone level, thus attempts to produce a smoother histogram. We also observed that the fuzzy IDS enhancement method performed better than the conventional IDS method.

## Conclusion:

In our research, we have extended a model of the human visual system based on conventional logic of black and white to a more powerful model of several gray levels (typically 256) using the concepts from fuzzy set theory.

We have also presented a new method for analyzing and comparing contrast enhancement algorithms.

Examining the evaluation evidence obtained from the presently known as well as our newly established enhancement quantification methods, we find the performance of our new image contrast enhancement method more satisfactory than the conventional method.

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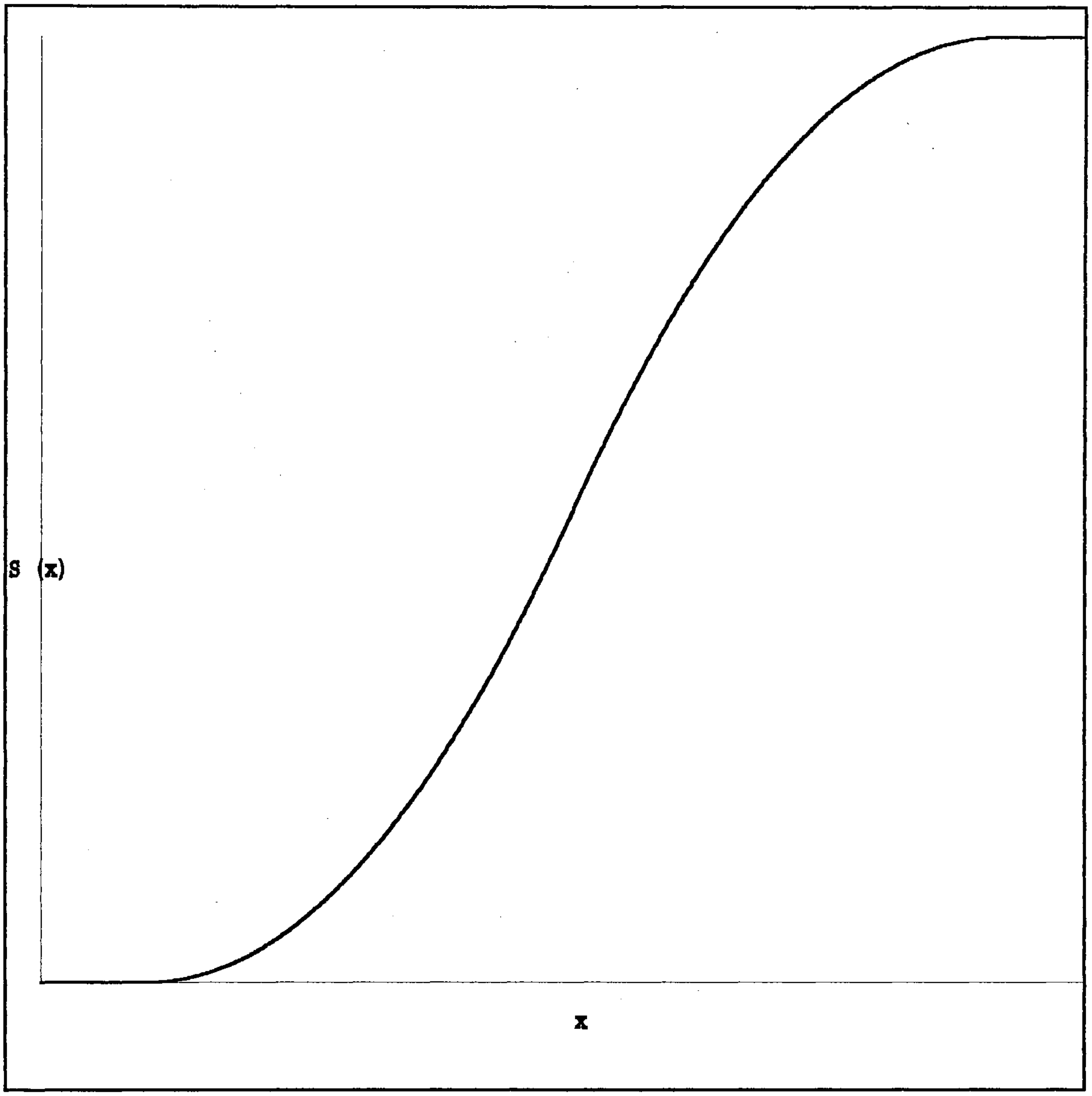
APPENDICES

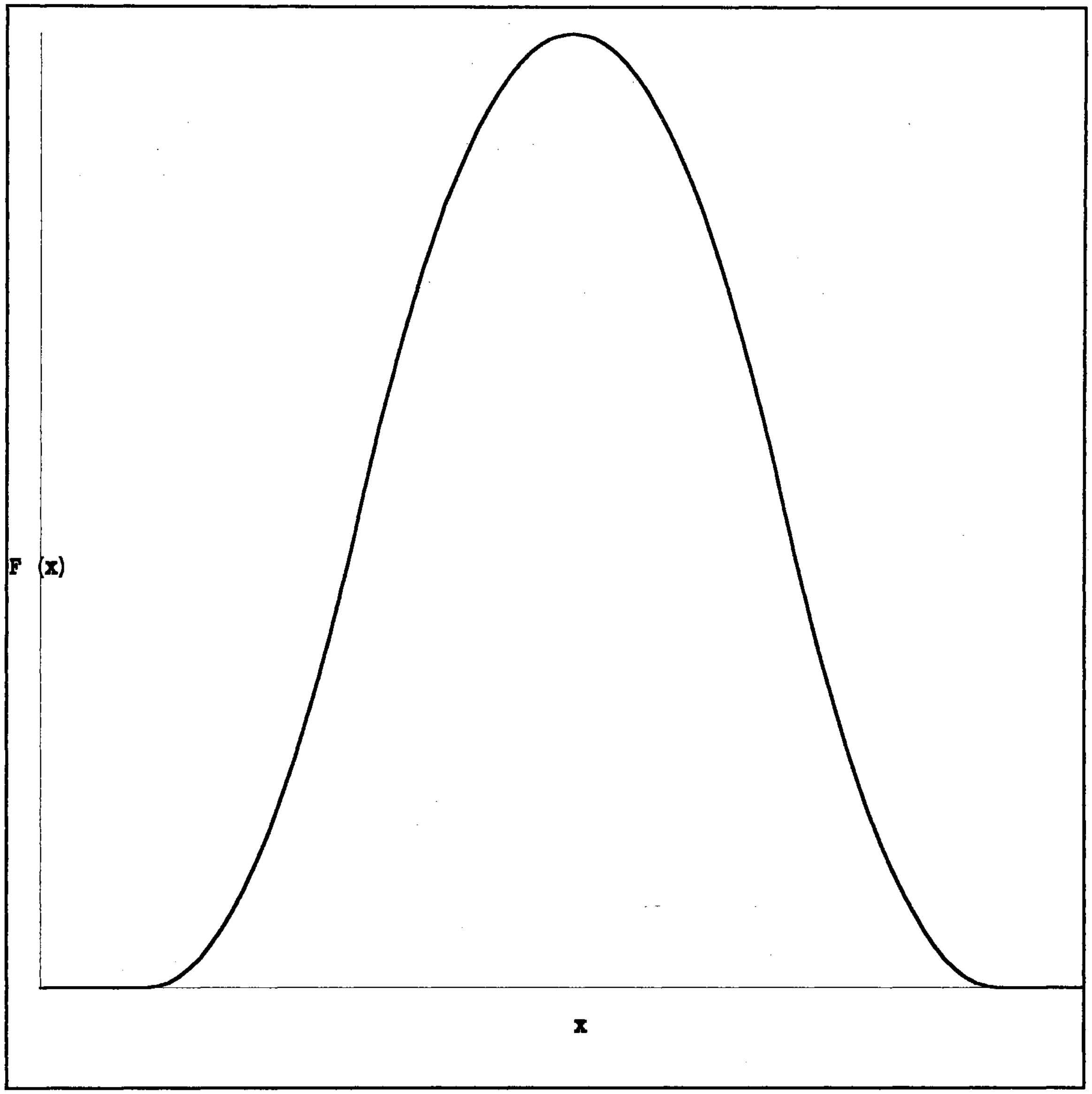
APPENDIX I-a

FUZZY MEMBERSHIP FUNCTION S



APPENDIX 1-b

FUZZY MEMBERSHIP FUNCTION F



# APPENDIX II

# IMAGES

Fig I-1-a: AIRPLANE
(original)

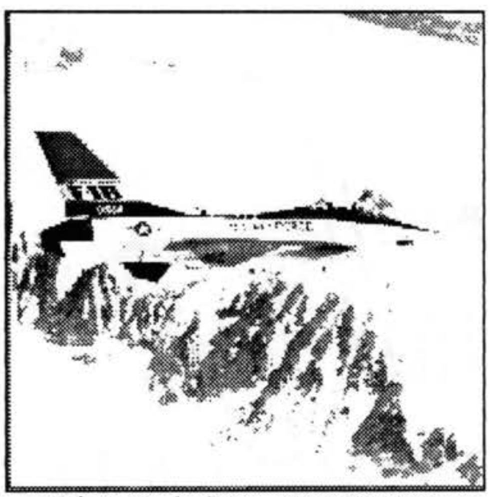


Fig I-1-b: AIRPLANE
(IDS enhanced)

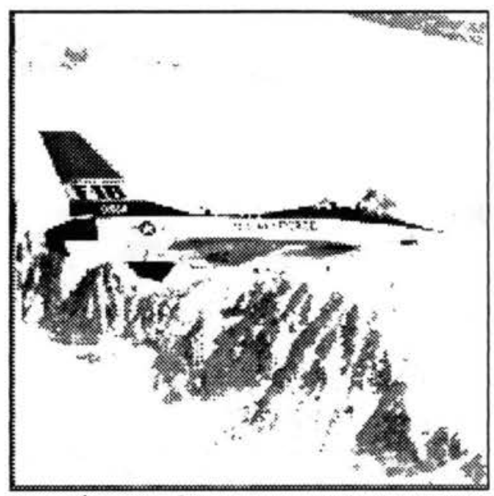


Fig I-1-c: AIRPLANE
(Fuzzy enhanced)

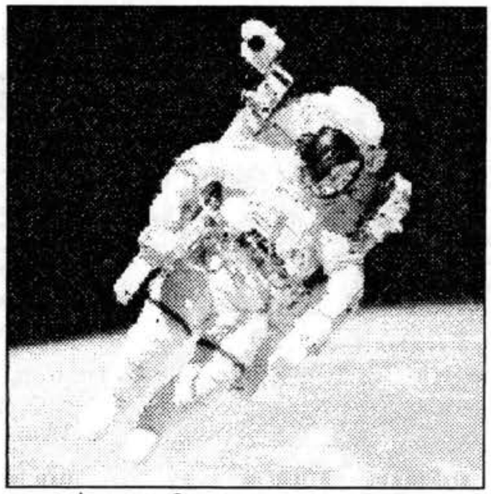


Fig I-2-a: ASTRONAT
(original)

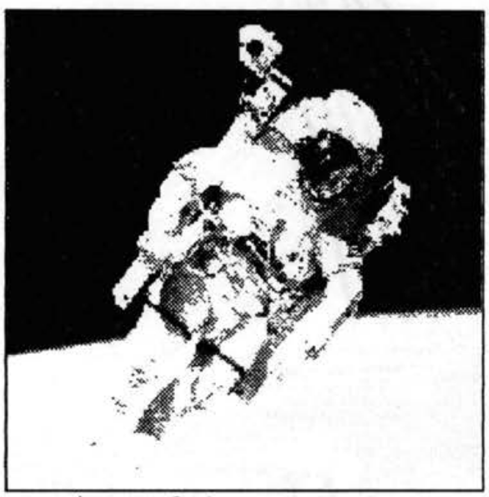


Fig I-2-b: ASTRONAT
(IDS enhanced)

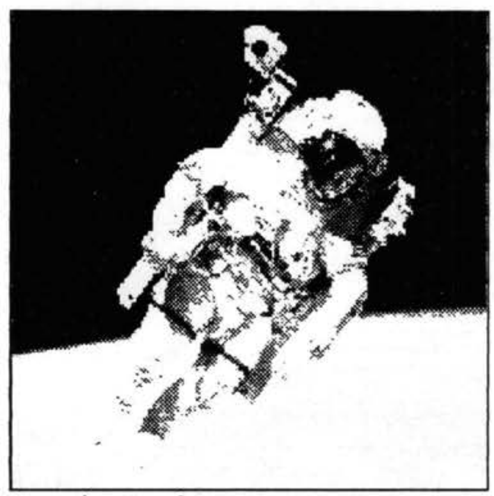


Fig I-2-c: ASTRONAT
(Fuzzy enhanced)

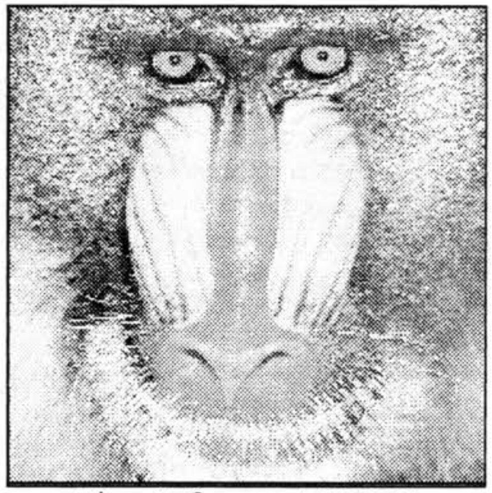


Fig I-3-a: BABOON
(original)

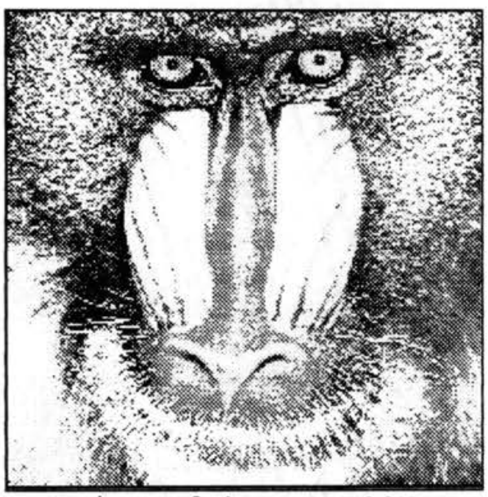


Fig I-3-b: BABOON
(IDS enhanced)

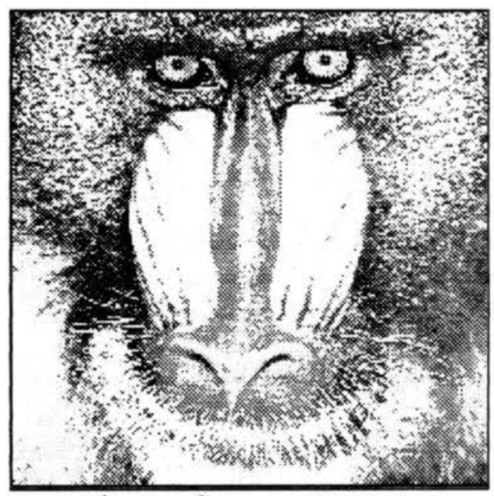


Fig I-3-c: BABOON
(Fuzzy enhanced)

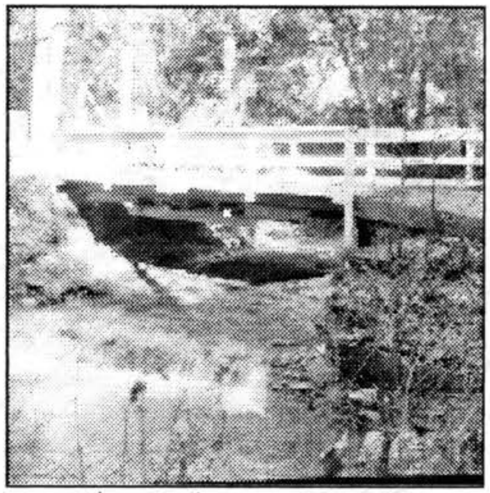


Fig I-4-a: BRIDGE
(original)

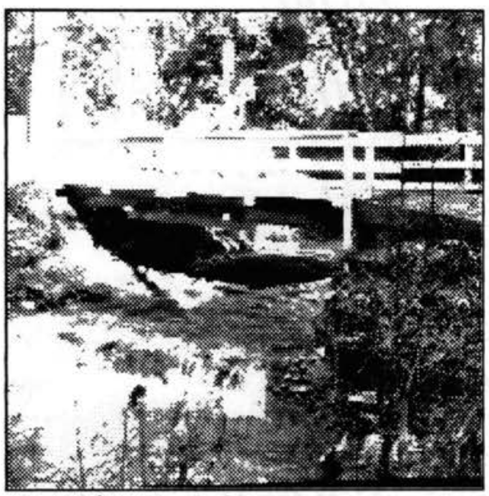


Fig I-4-b: BRIDGE
(IDS enhanced)

Fig I-4-c: BRIDGE
(Fuzzy enhanced)

Fig I-5-a: CAMERA
(original)

Fig I-5-b: CAMERA
(IDS enhanced)

Fig I-5-c: CAMERA
(Fuzzy enhanced)

Fig I-6-a: COUPLE
(original)

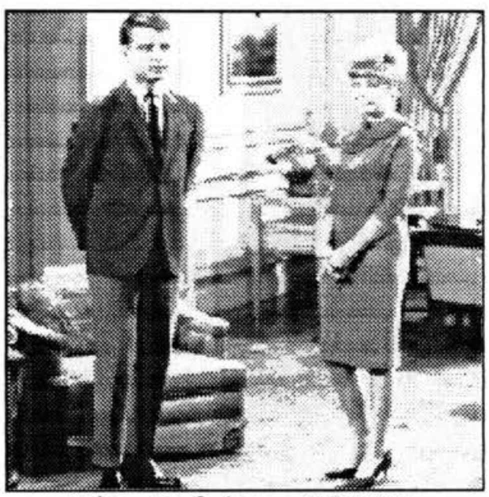


Fig I-6-b: COUPLE
(IDS enhanced)

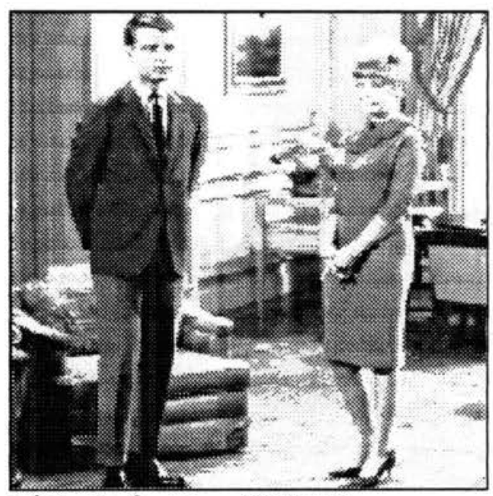


Fig I-6-c: COUPLE
(Fuzzy enhanced)

Fig I-7-a: GIRL
(original)

Fig I-7-b: GIRL
(IDS enhanced)

Fig I-7-c: GIRL
(Fuzzy enhanced)

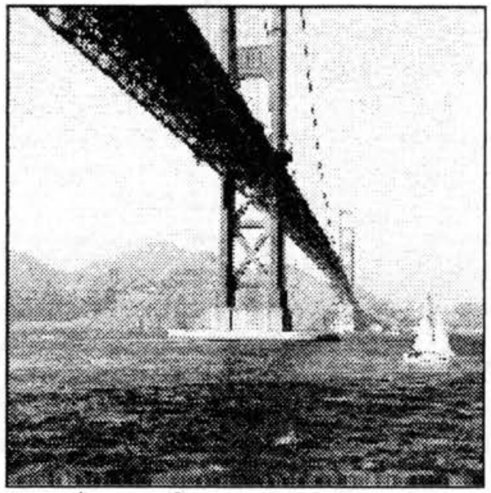


Fig I-8-a: GOLDNGAT
(original)

Fig I-8-b: GOLDNGAT
(IDS enhanced)

Fig I-8-c: GOLDNGAT
(Fuzzy enhanced)

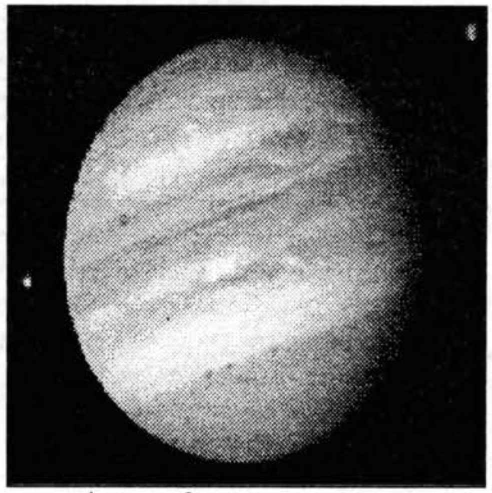


Fig I-9-a: JUPITER
(original)

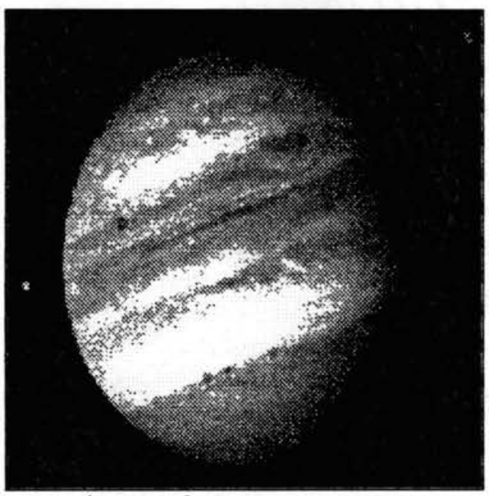


Fig I-9-b: JUPITER
(IDS enhanced)

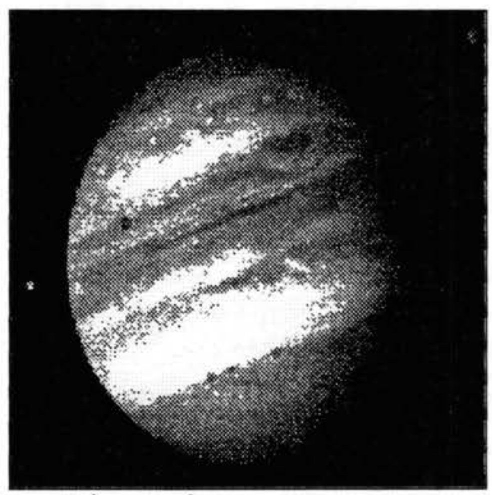


Fig I-9-c: JUPITER
(Fuzzy enhanced)

Fig I-10-a: LENA
(original)

Fig I-10-b: LENA
(IDS enhanced)

Fig I-10-c: LENA
(Fuzzy enhanced)

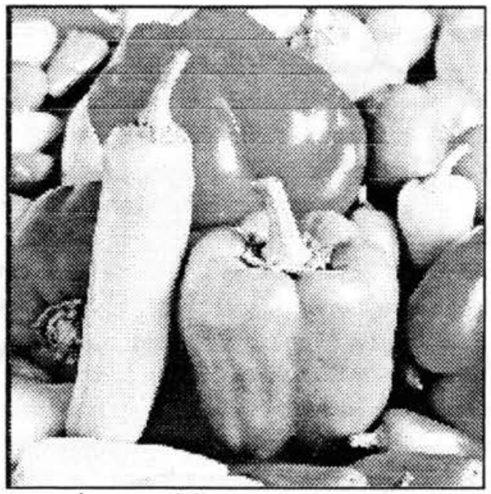


Fig I-11-a: PEPPERS
(original)

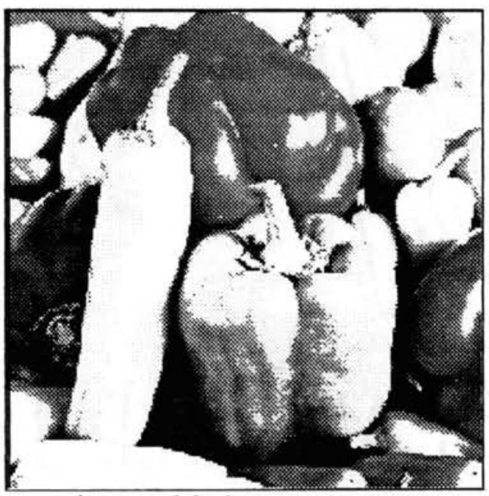


Fig I-11-b: PEPPERS
(IDS enhanced)

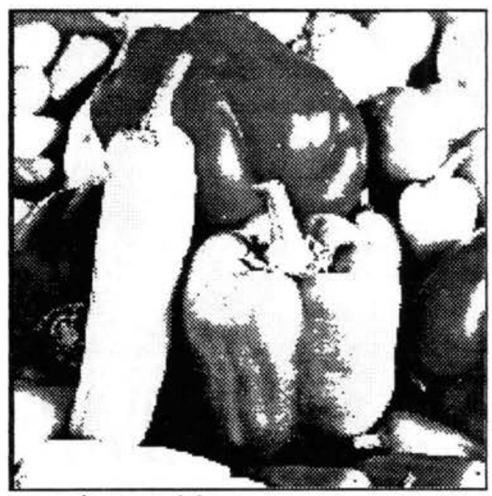


Fig I-11-c: PEPPERS
(Fuzzy enhanced)

APPENDIX III

HISTOGRAMS

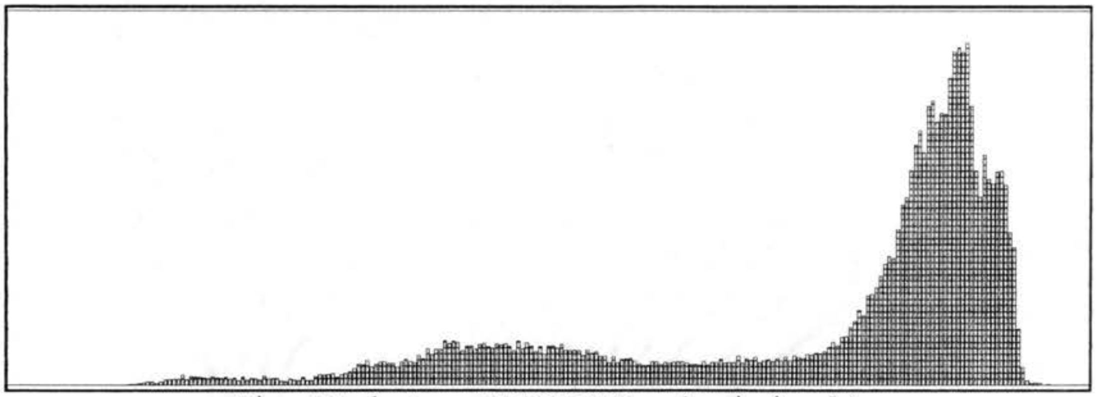


Fig II-1-a: AIRPLANE (original)

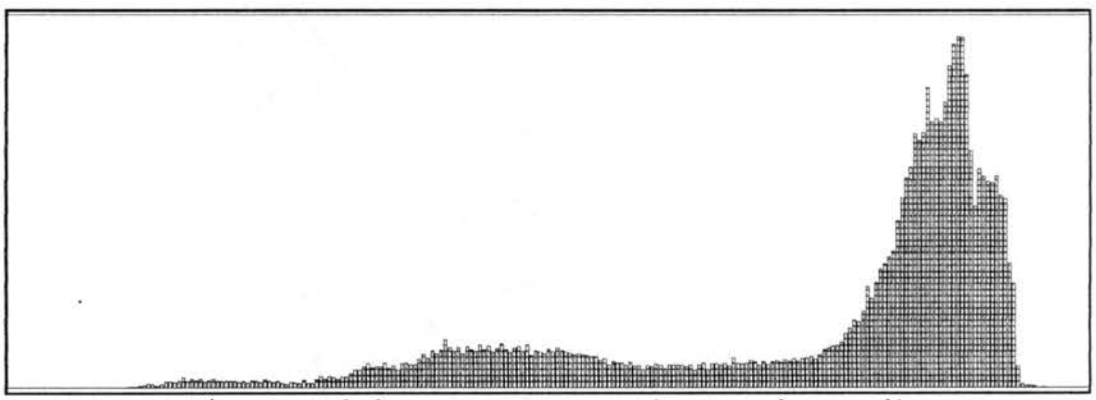


Fig III-1-b: AIRPLANE (IDS enhanced)

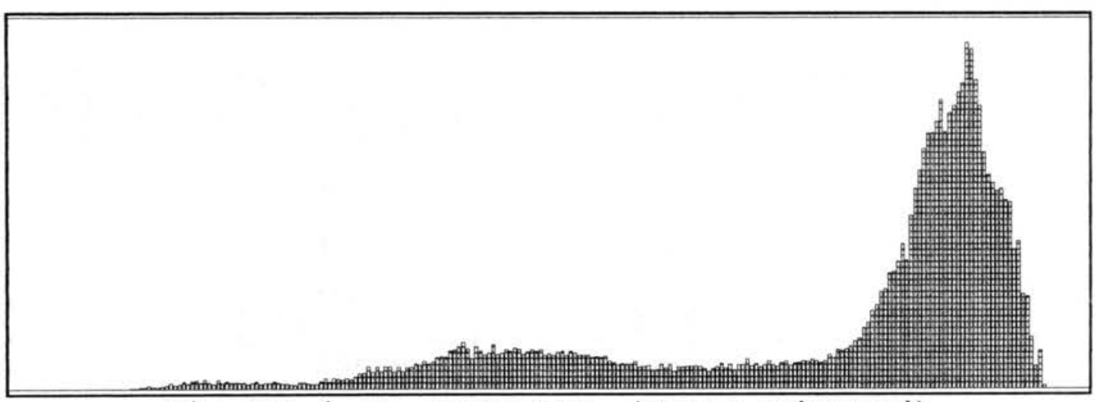


Fig III-1-c: AIRPLANE (Fuzzy enhanced)

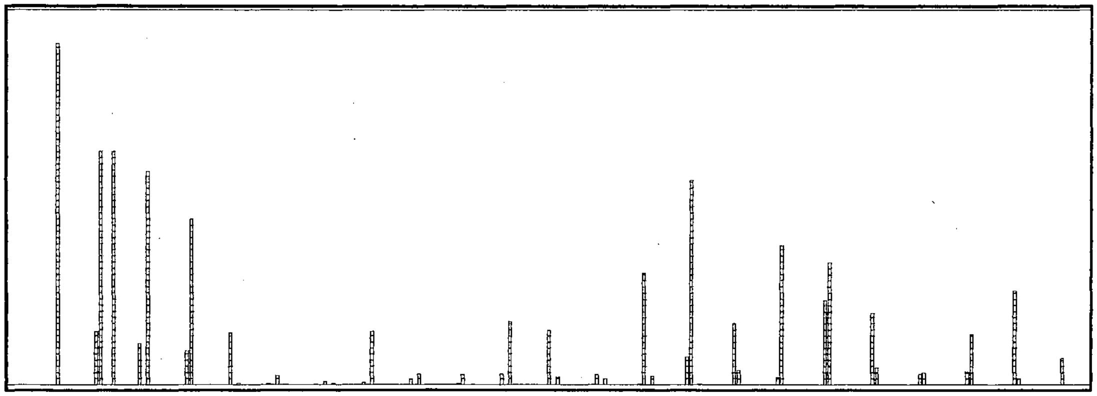


Fig III-2-a: ASTRONAT (original)

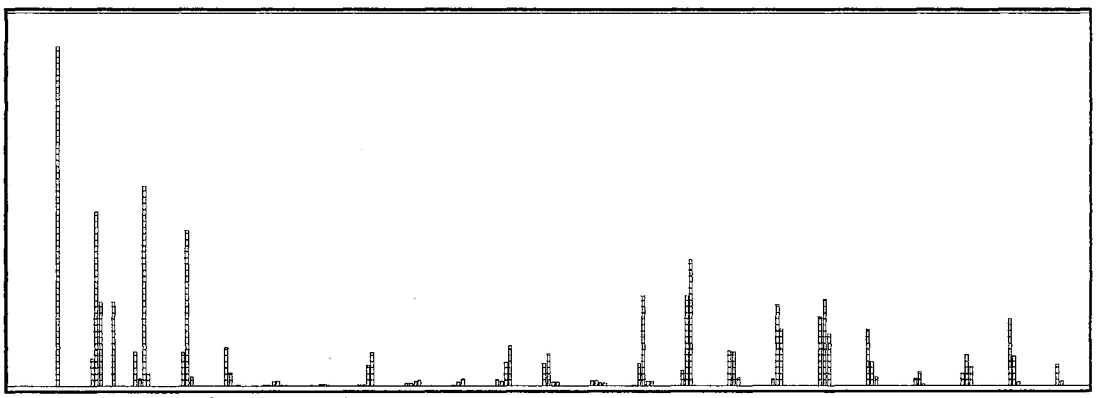


Fig III-2-b: ASTRONAT (IDS enhanced)

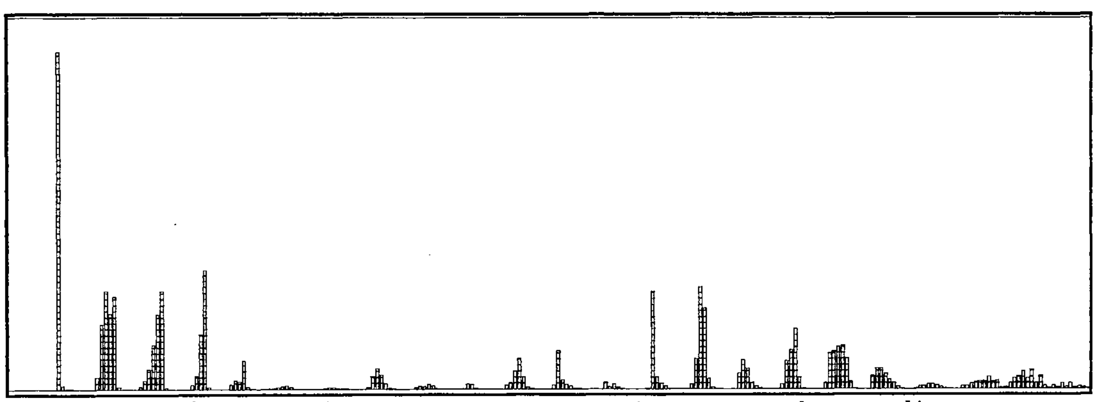


Fig III-2-c: ASTRONAT (Fuzzy enhanced)

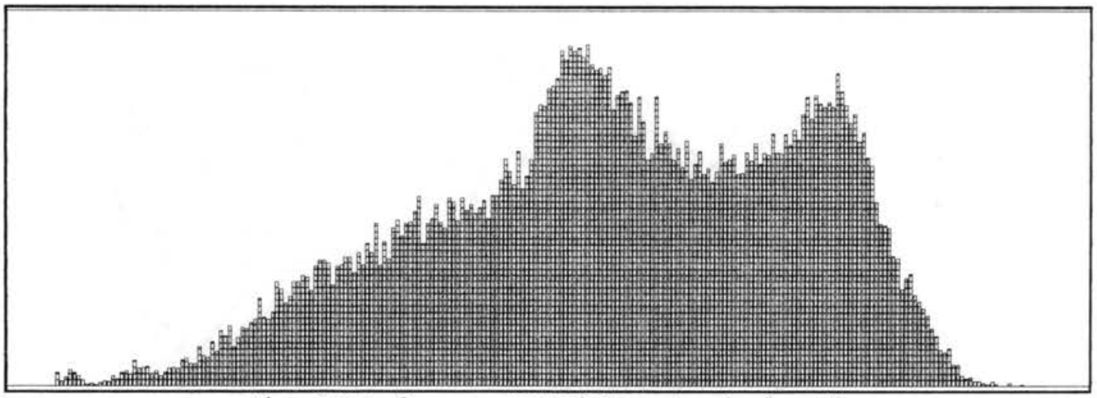


Fig III-3-a: BABOON (original)

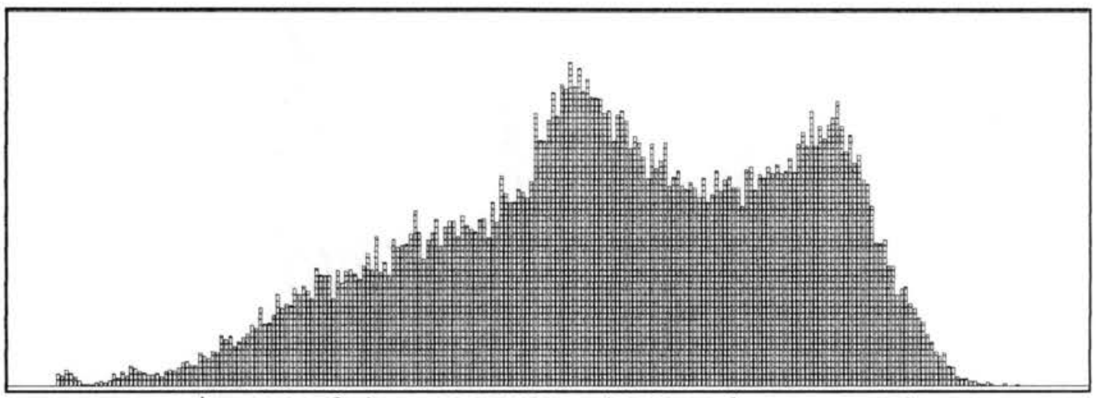


Fig III-3-b: BABOON (IDS enhancement)

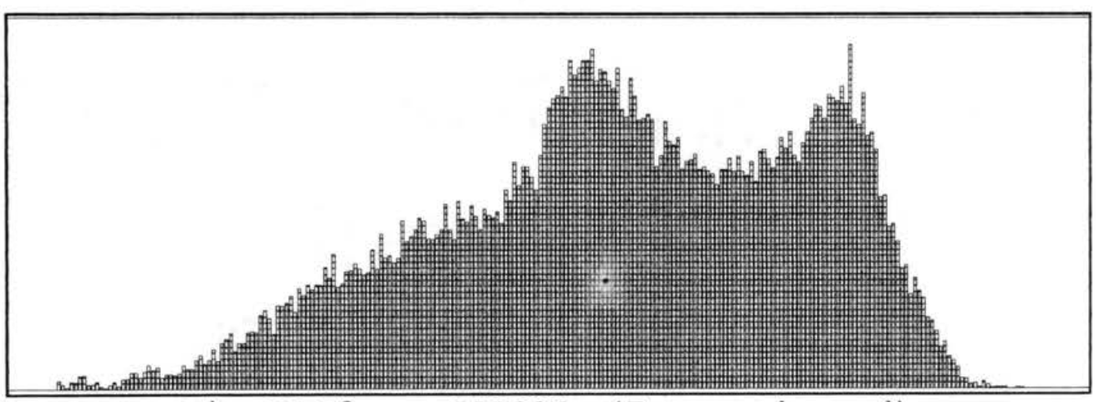


Fig III-3-c: BABOON (Fuzzy enhanced)

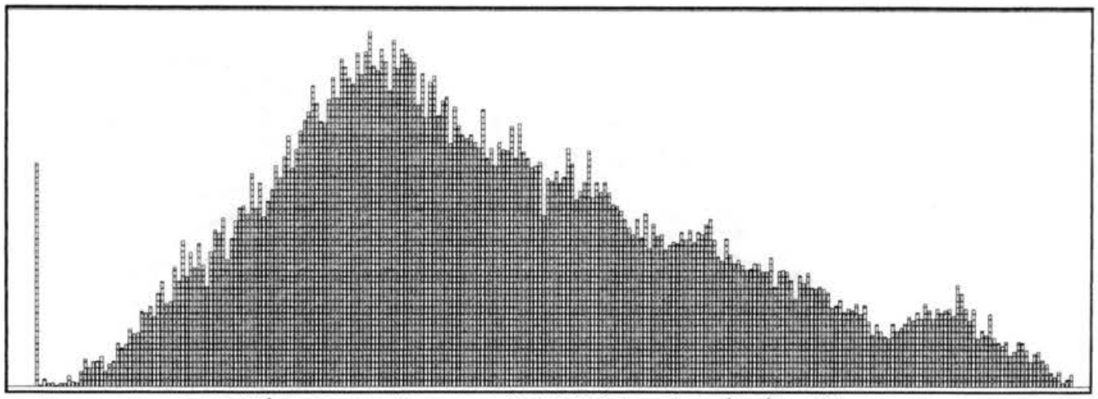


Fig III-4-a: BRIDGE (original)

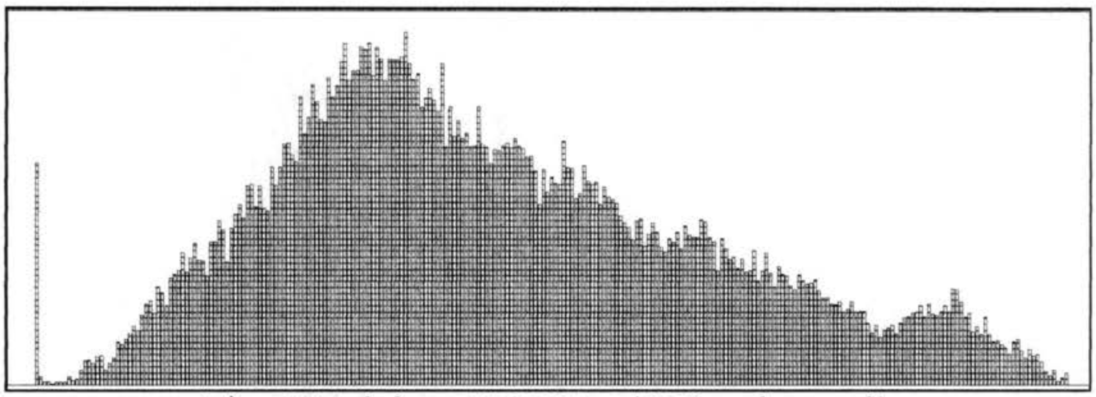


Fig III-4-b: BRIDGE (IDS enhanced)

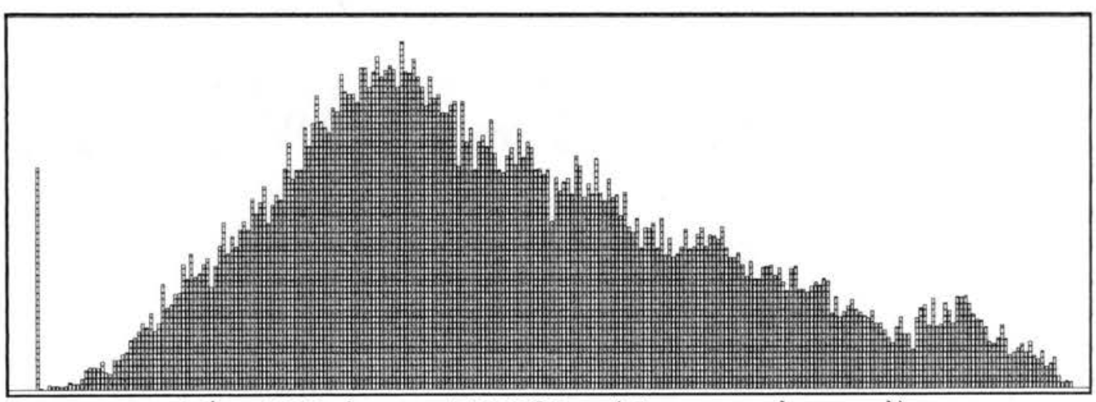


Fig III-4-c: BRIDGE (Fuzzy enhanced)

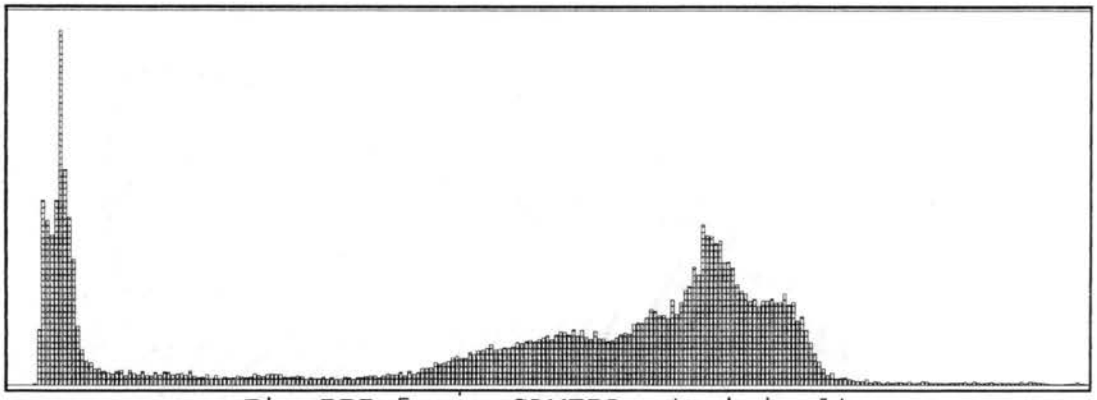


Fig III-5-a: CAMERA (original)

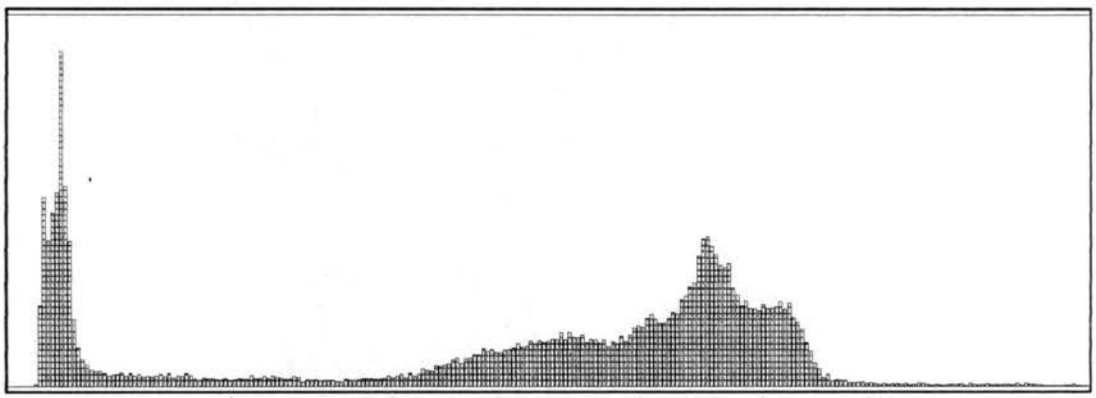


Fig III-5-b: CAMERA (IDS enhanced)

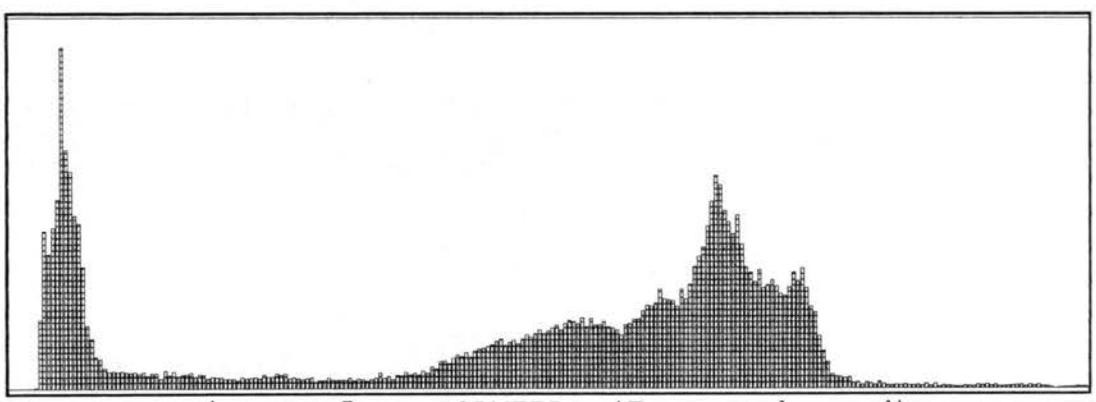


Fig III-5-c: CAMERA (Fuzzy enhanced)

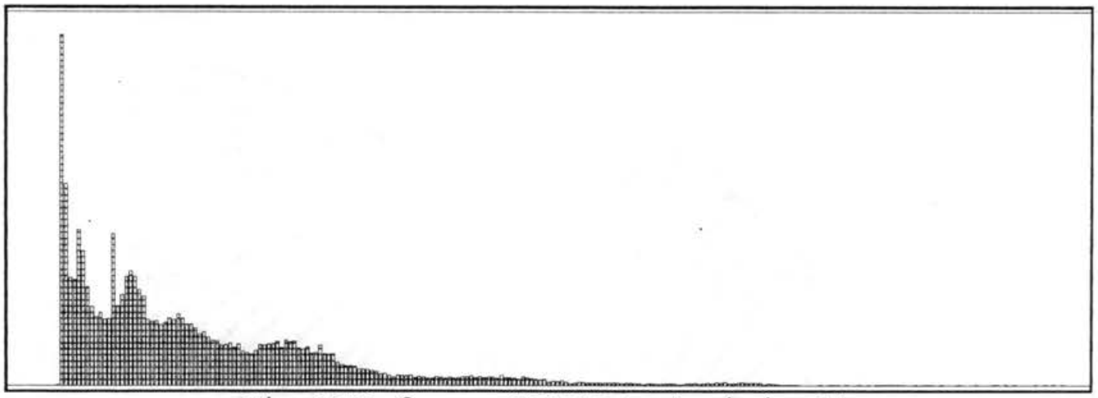


Fig III-6-a: COUPLE (original)

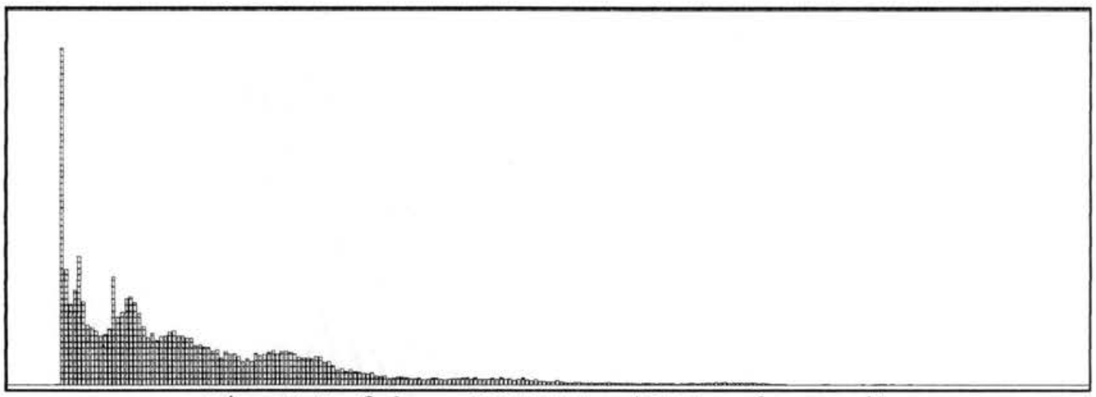


Fig III-6-b: COUPLE (IDS enhanced)

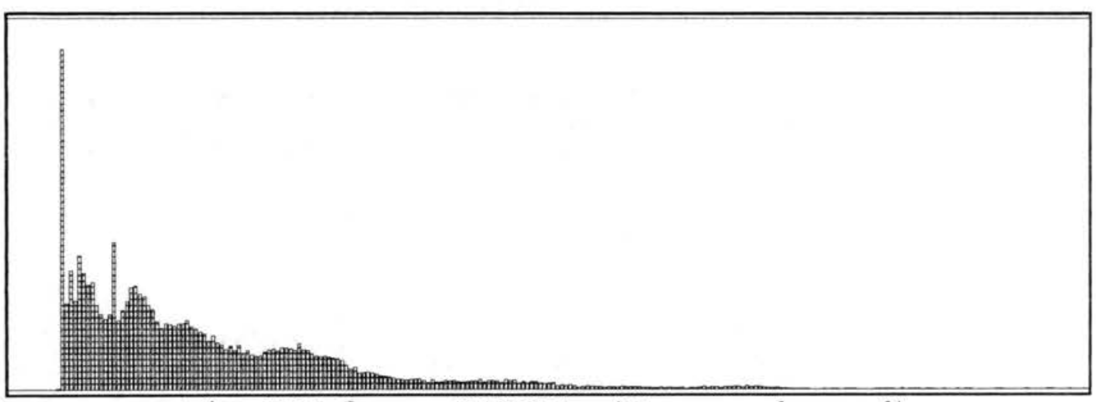


Fig III-6-c: COUPLE (Fuzzy enhanced)

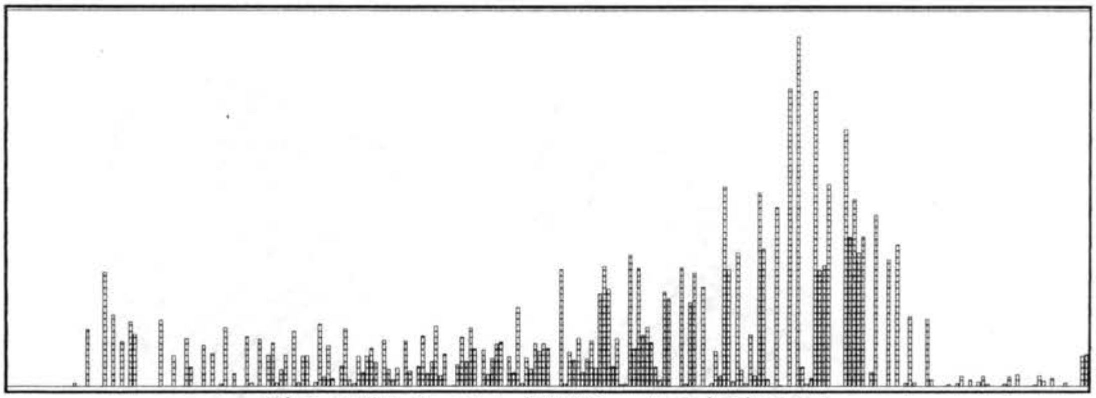


Fig III-7-a: GIRL (original)

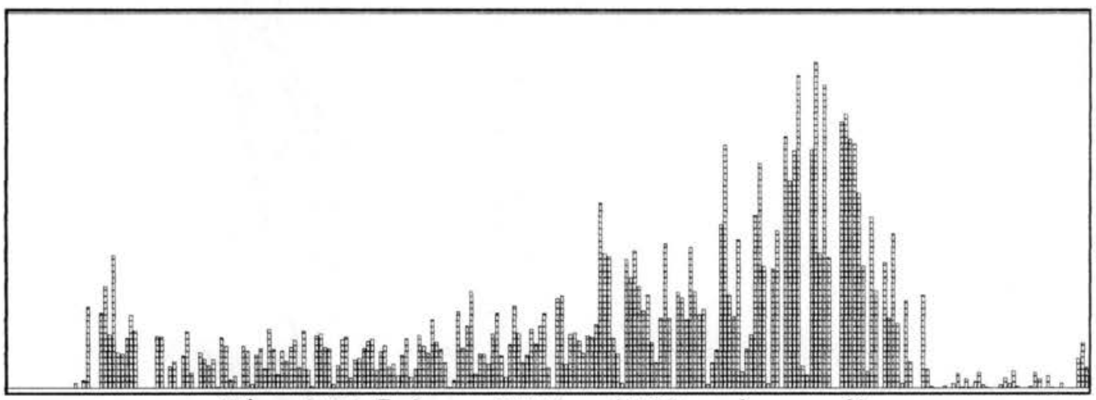


Fig III-7-b: GIRL (IDS enhanced)

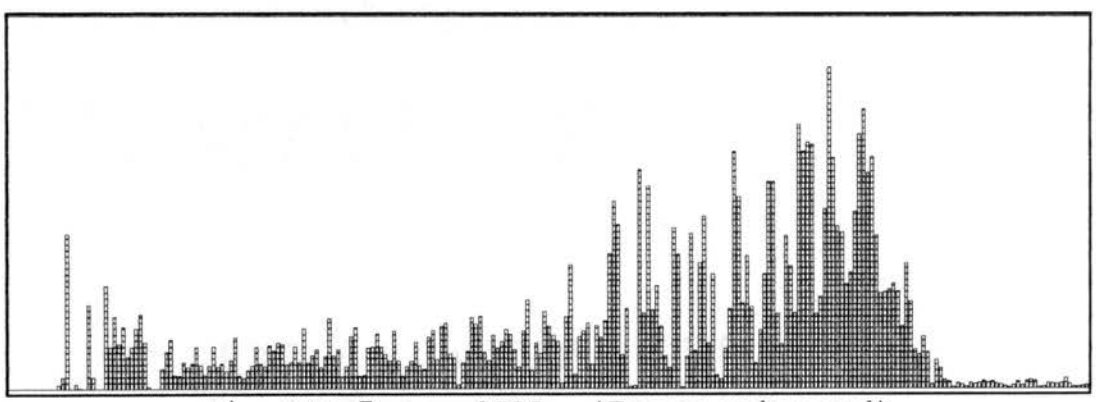


Fig III-7-c: GIRL (Fuzzy enhanced)

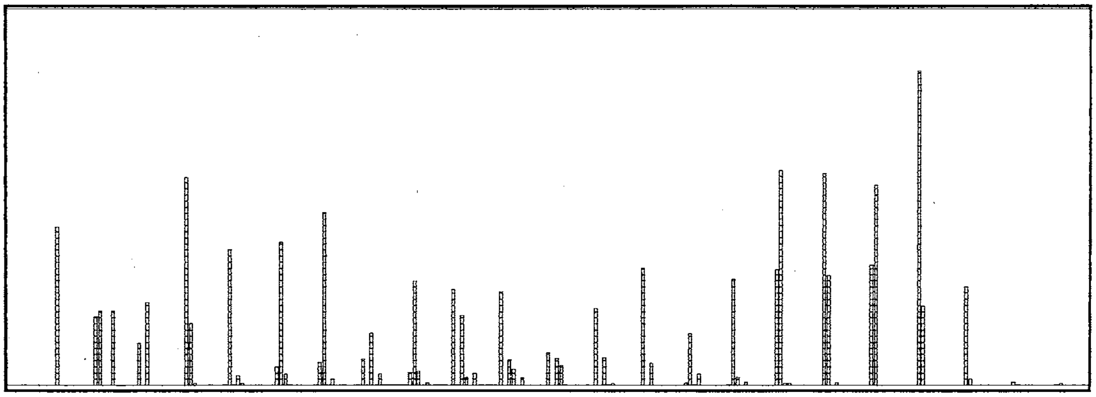


Fig III-8-a: GOLDNGAT (original)

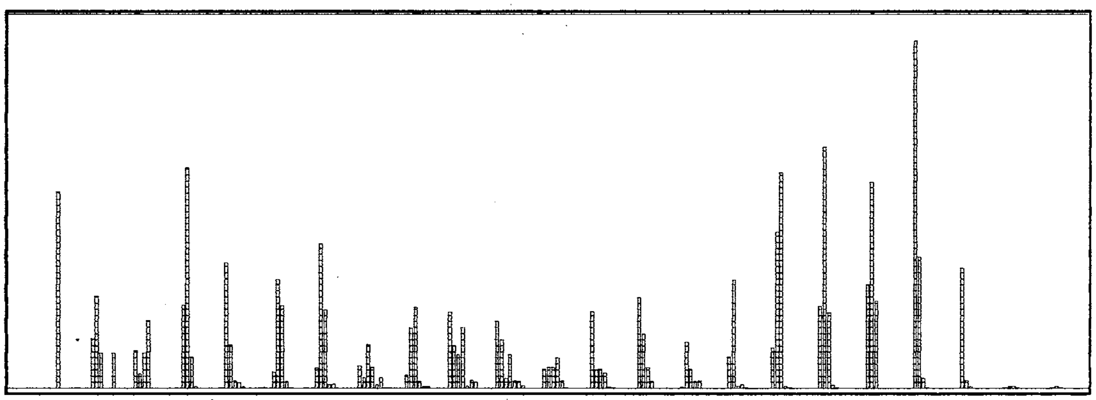


Fig III-8-b: GOLDNGAT (IDS enhanced)

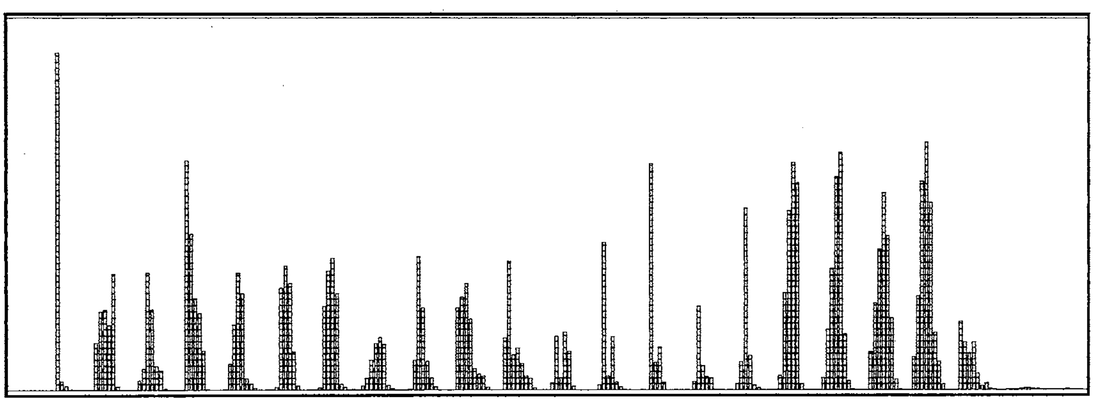


Fig III-8-c: GOLDNGAT (Fuzzy enhanced)

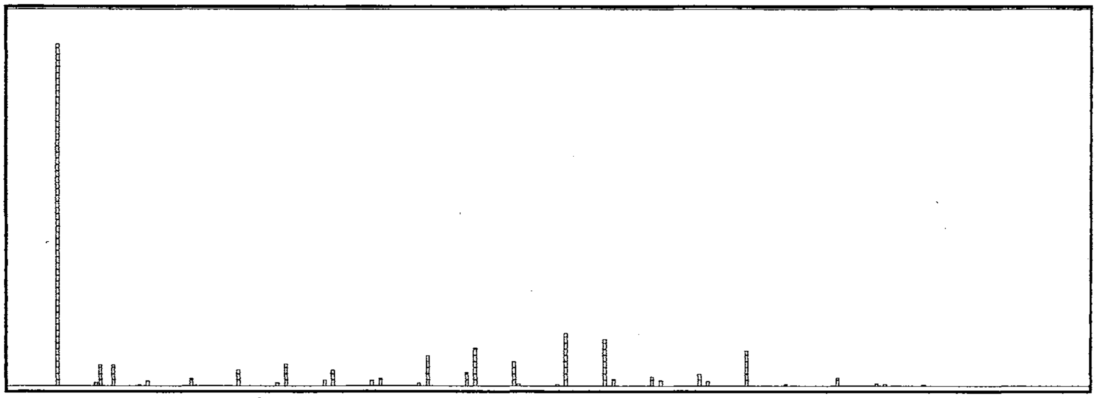


Fig III-9-a: JUPITER (original)

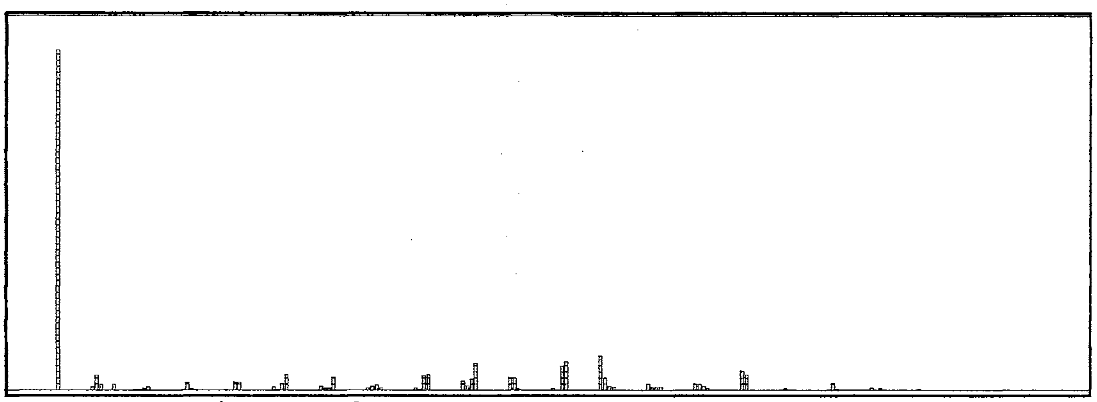


Fig III-9-b: JUPITER (IDS enhanced)

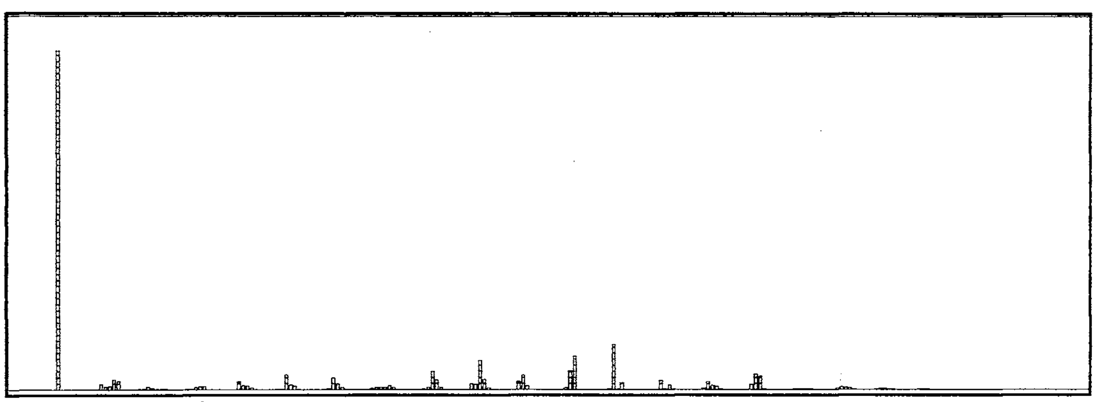


Fig III-9-c: JUPITER (Fuzzy enhanced)

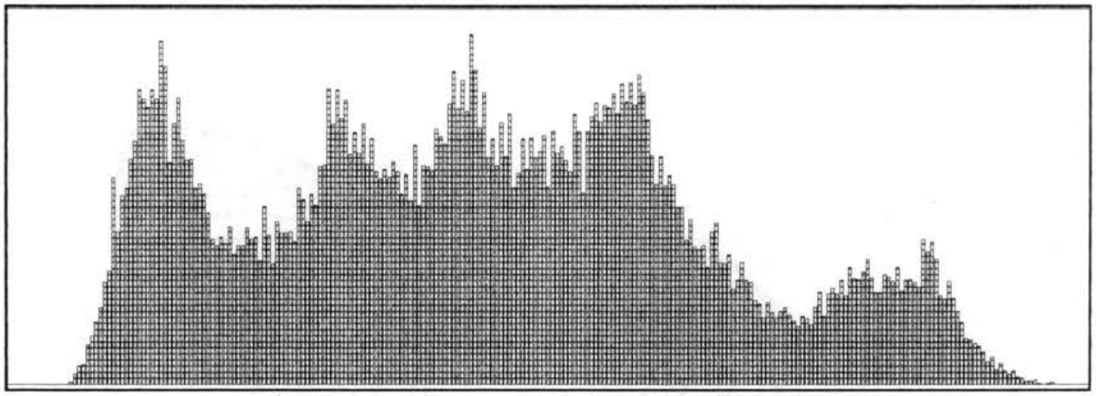


Fig III-10-a: LENA (original)

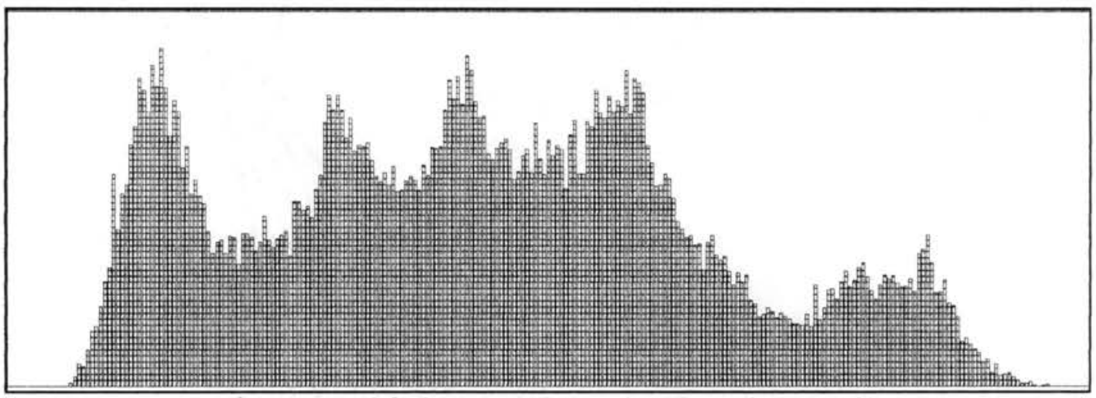


Fig III-10-b: LENA (IDS enhanced)

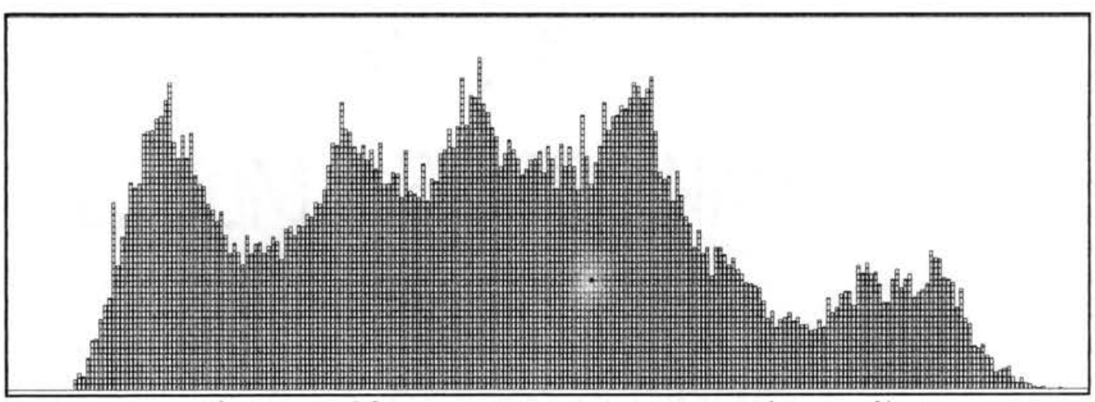


Fig III-10-c: LENA (Fuzzy enhanced)

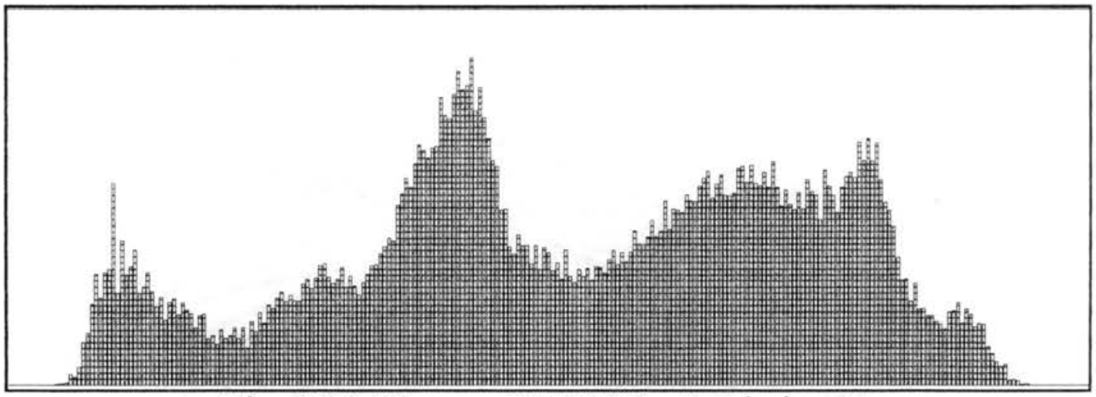


Fig III-11-a: PEPPERS (original)

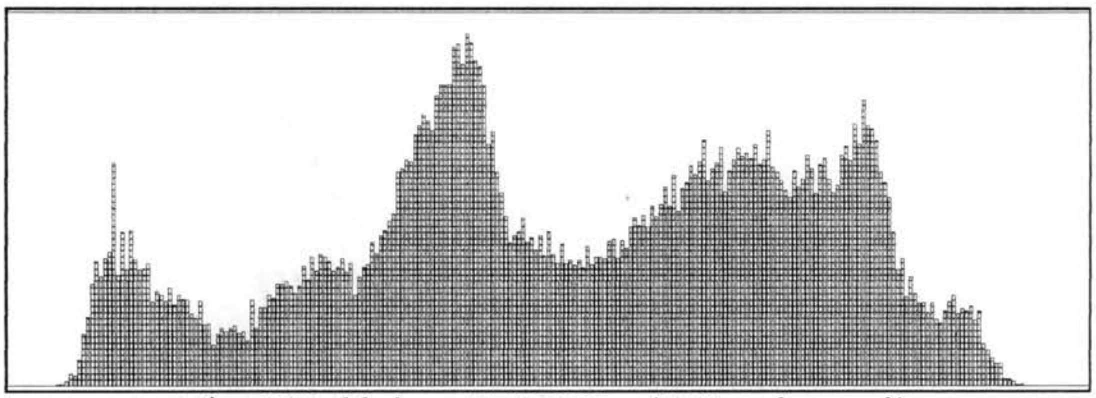


Fig III-11-b: PEPPERS (IDS enhanced)

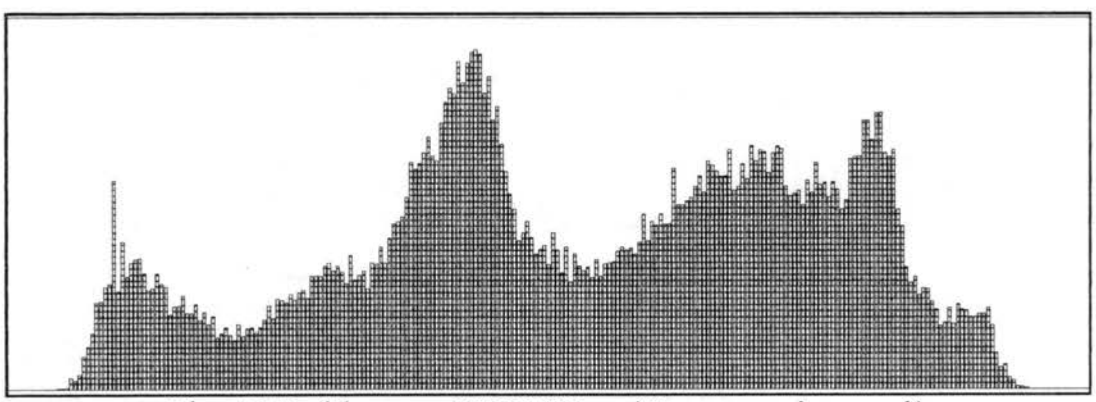


Fig III-11-c: PEPPERS (Fuzzy enhanced)

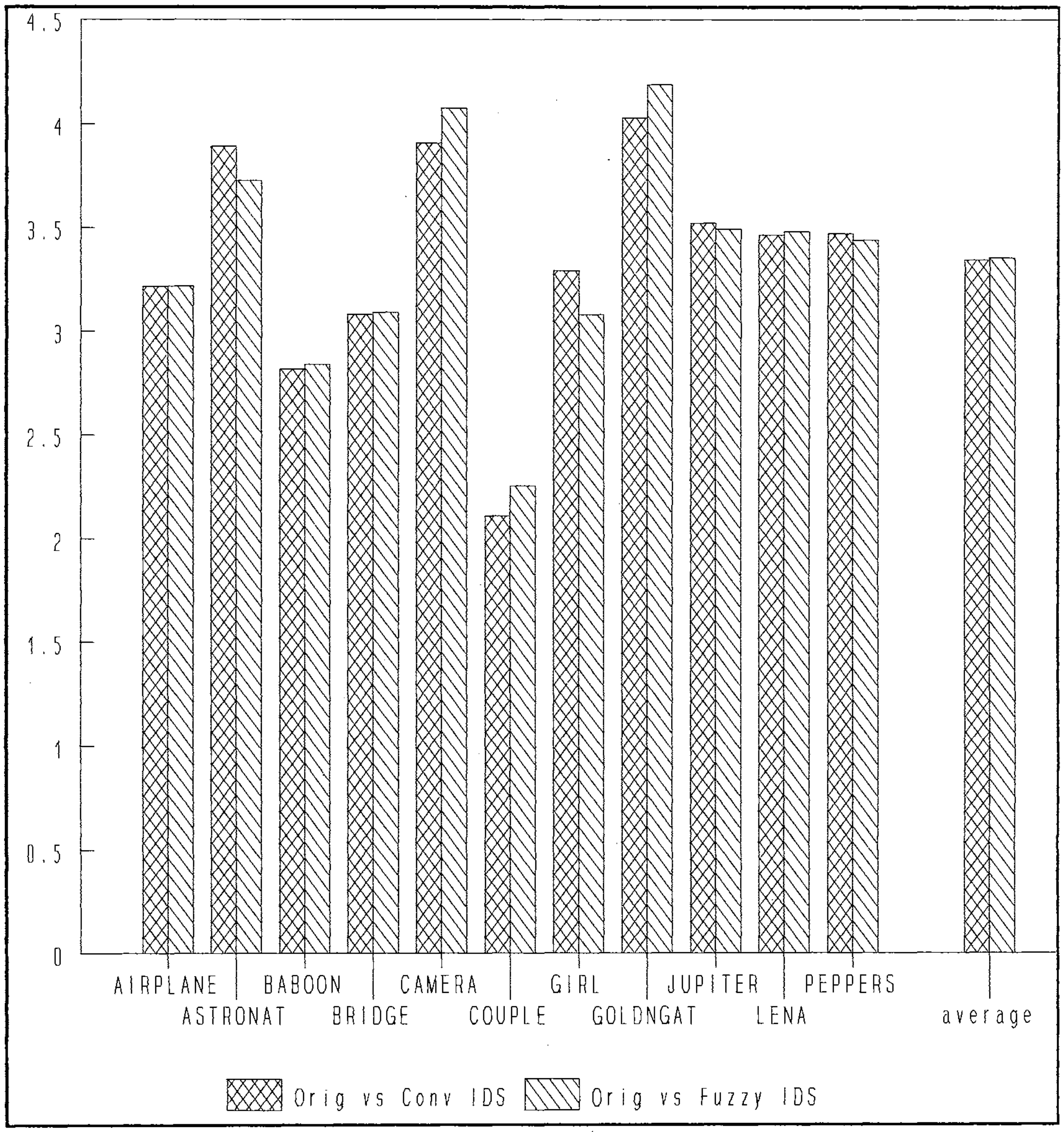
## APPENDIX IV-a

## ERROR ROOT MEAN SQUARE ANALYSIS
(numerical form)

| | *Original vs Conventional IDS* | *Original vs Fuzzy IDS* |
|---|---|---|
| AIRPLANE | 3.215503 | 3.218820 |
| ASTRONAT | 3.890778 | 3.725004 |
| BABOON | 2.816534 | 2.839312 |
| BRIDGE | 3.081596 | 3.092245 |
| CAMERA | 3.906126 | 4.072453 |
| COUPLE | 2.110293 | 2.255526 |
| GIRL | 3.294765 | 3.080328 |
| GOLDNGAT | 4.027278 | 4.191188 |
| JUPITER | 3.522972 | 3.497715 |
| LENA | 3.467250 | 3.485799 |
| PEPPERS | 3.475171 | 3.442055 |
| average | 3.346206 | 3.354586 |

APPENDIX IV-b

ERROR ROOT MEAN SQUARE ANALYSIS
(graphical form)



APPENDIX V

BIMODALITY ANALYSIS

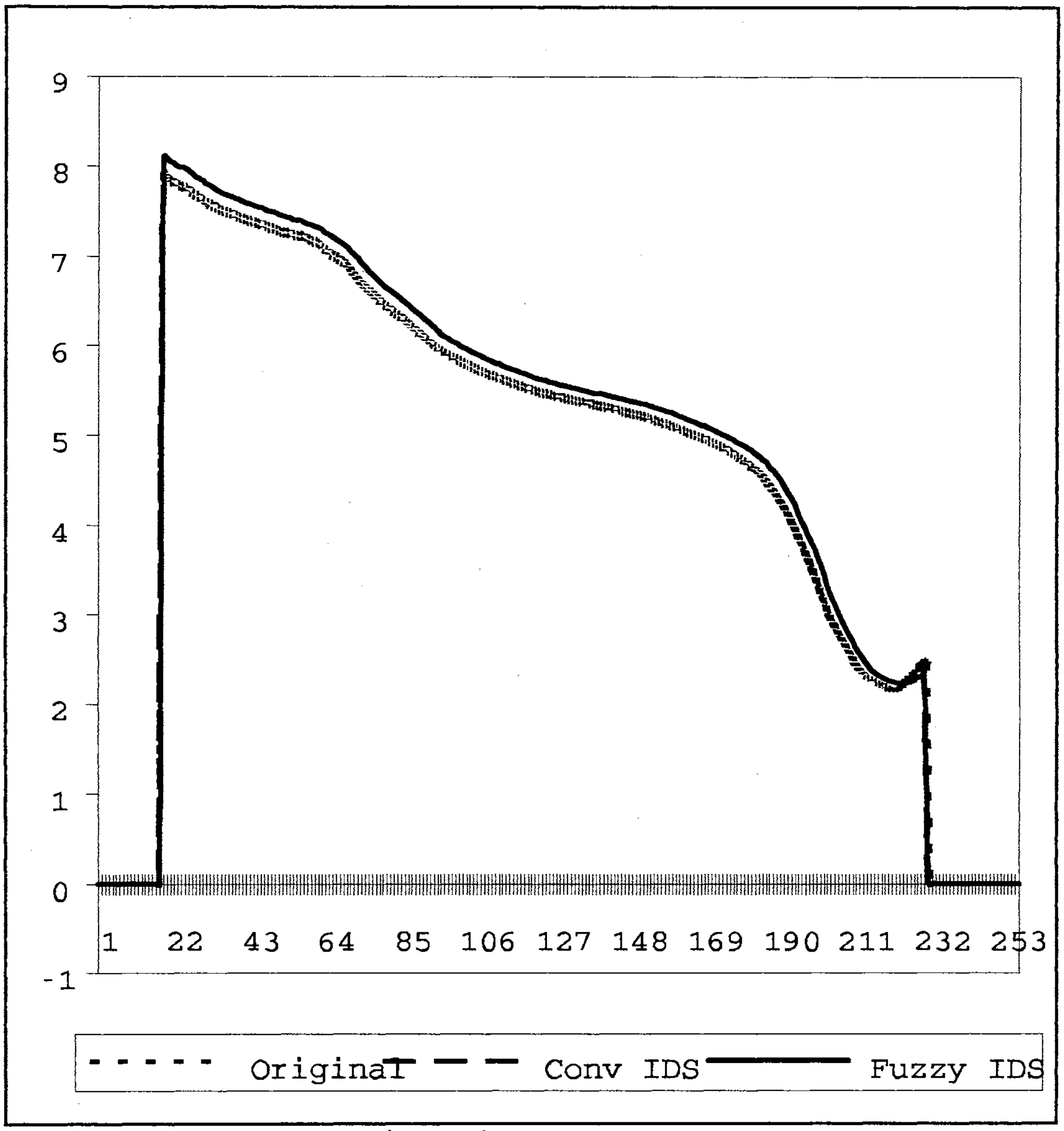



Fig V-1: AIRPLANE

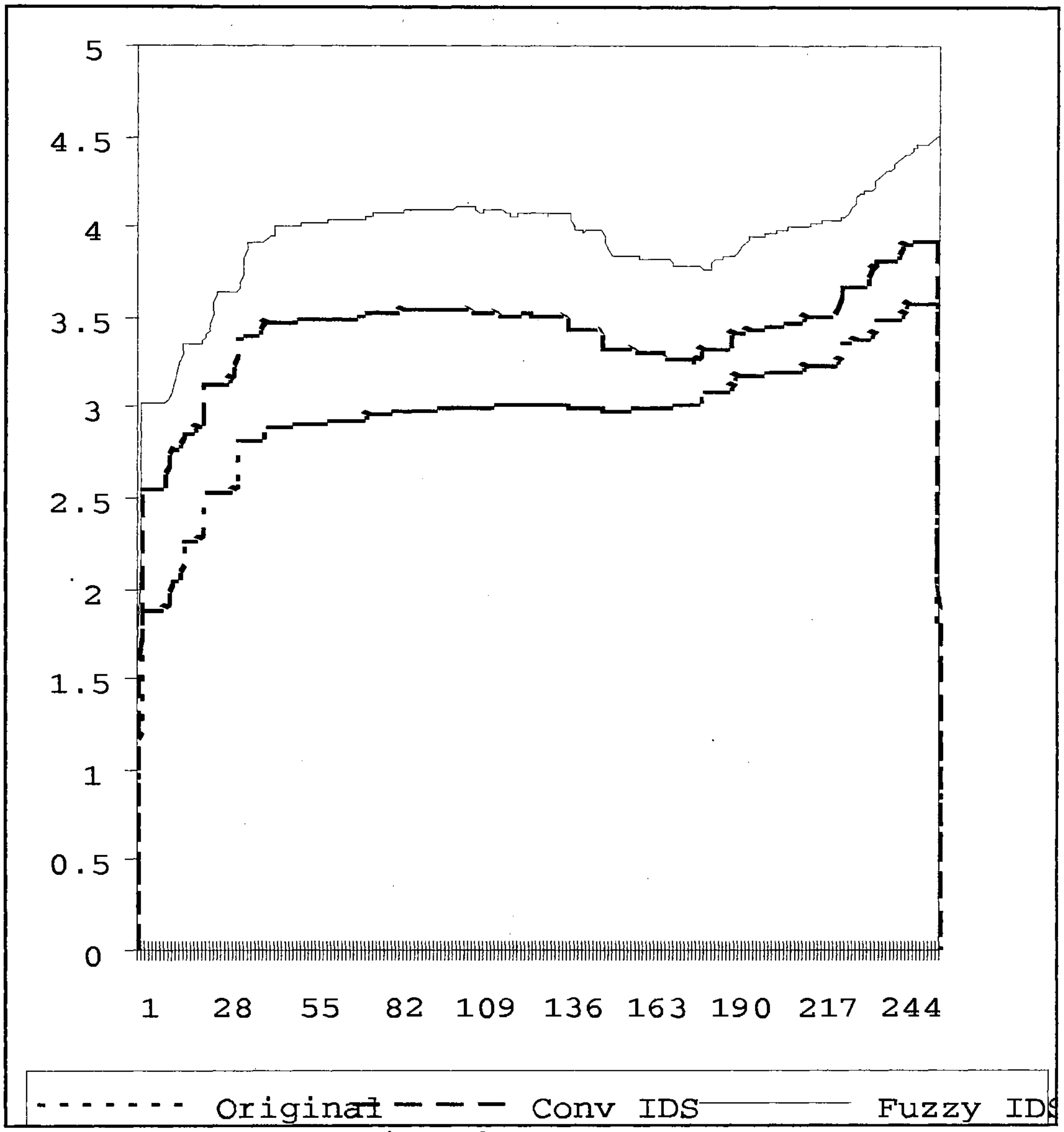



Fig V-2: ASTRONAT

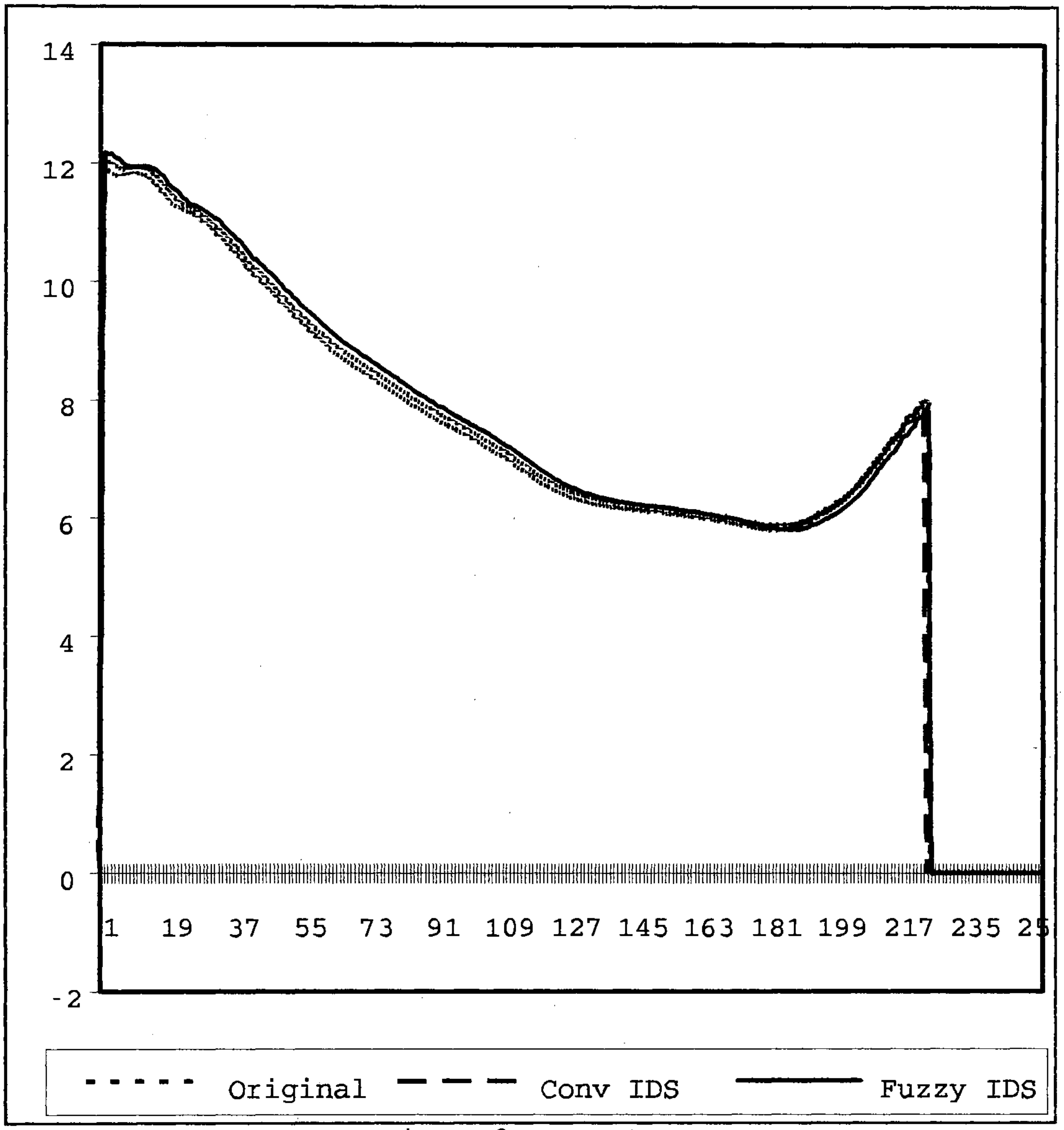



Fig V-3: BABOON

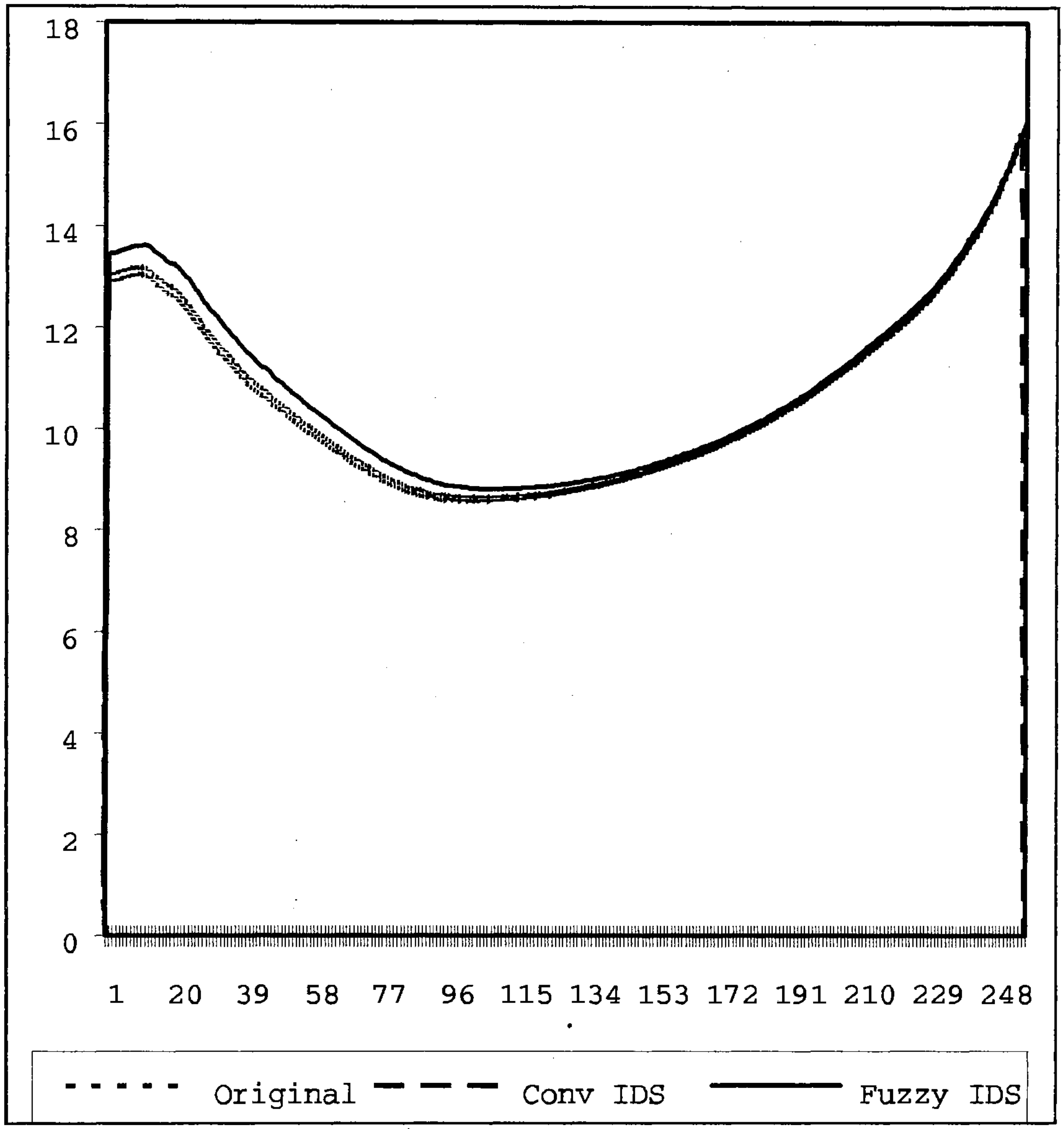



Fig V-4: BRIDGE

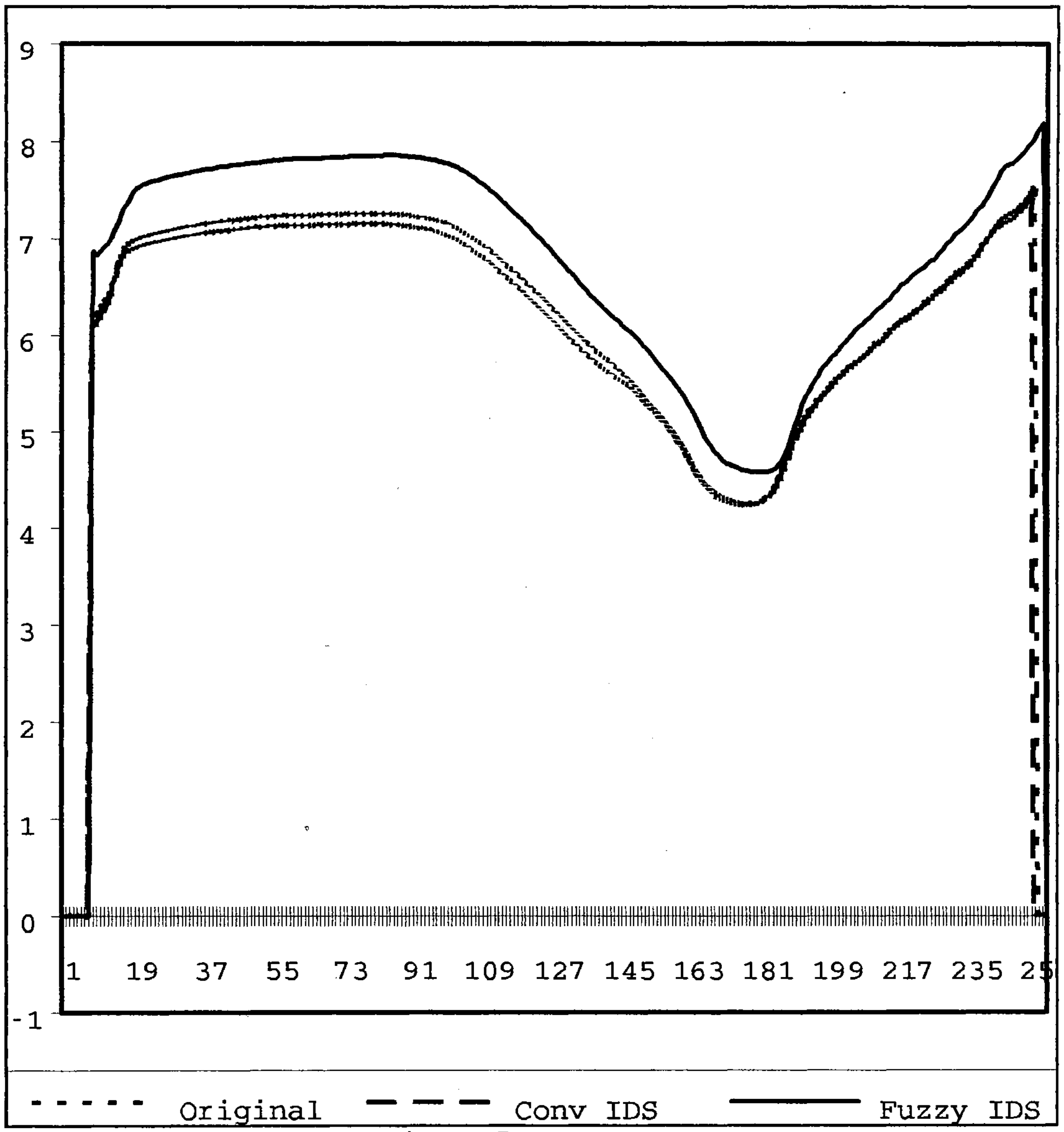



Fig V-5: CAMERA

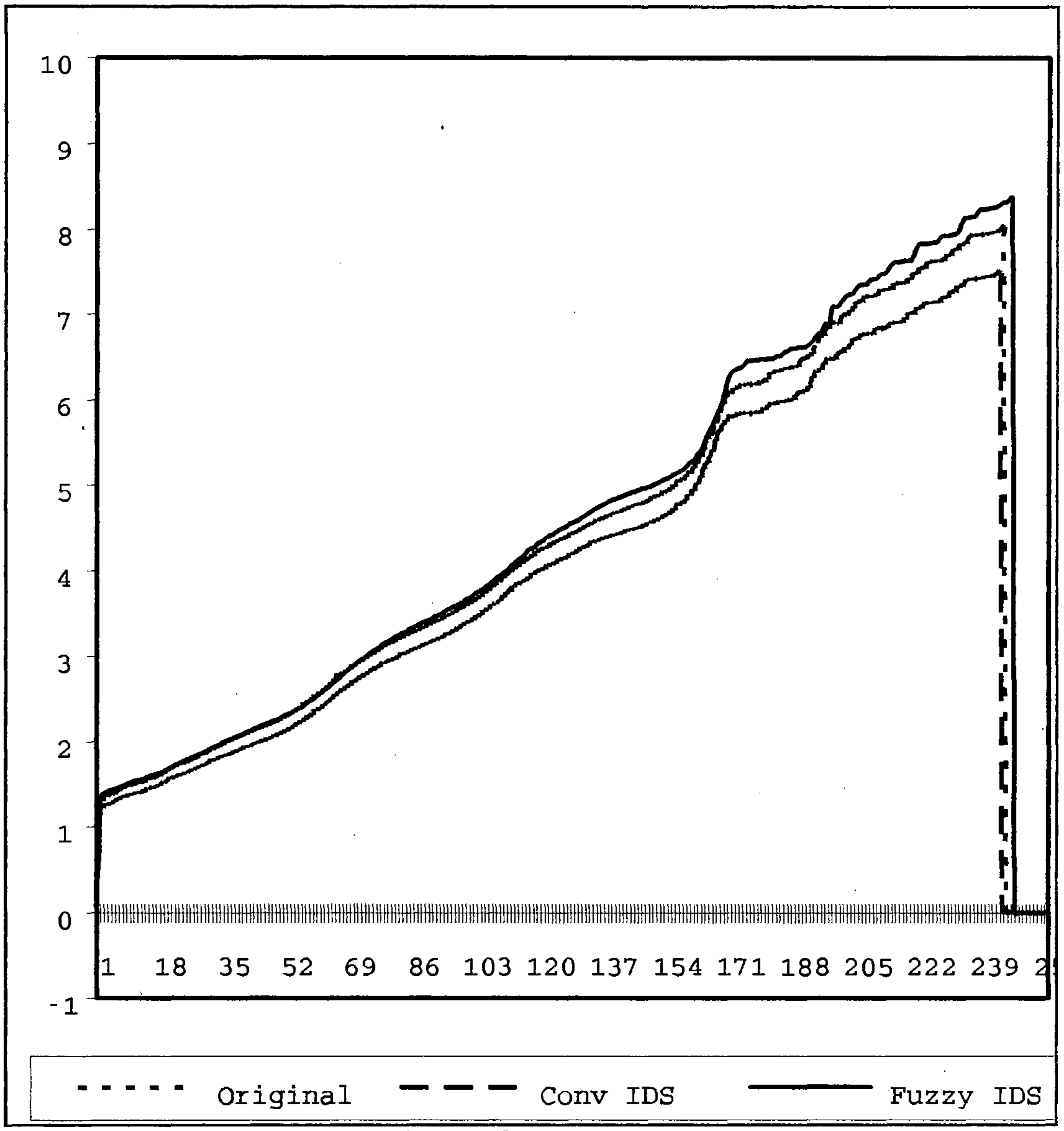
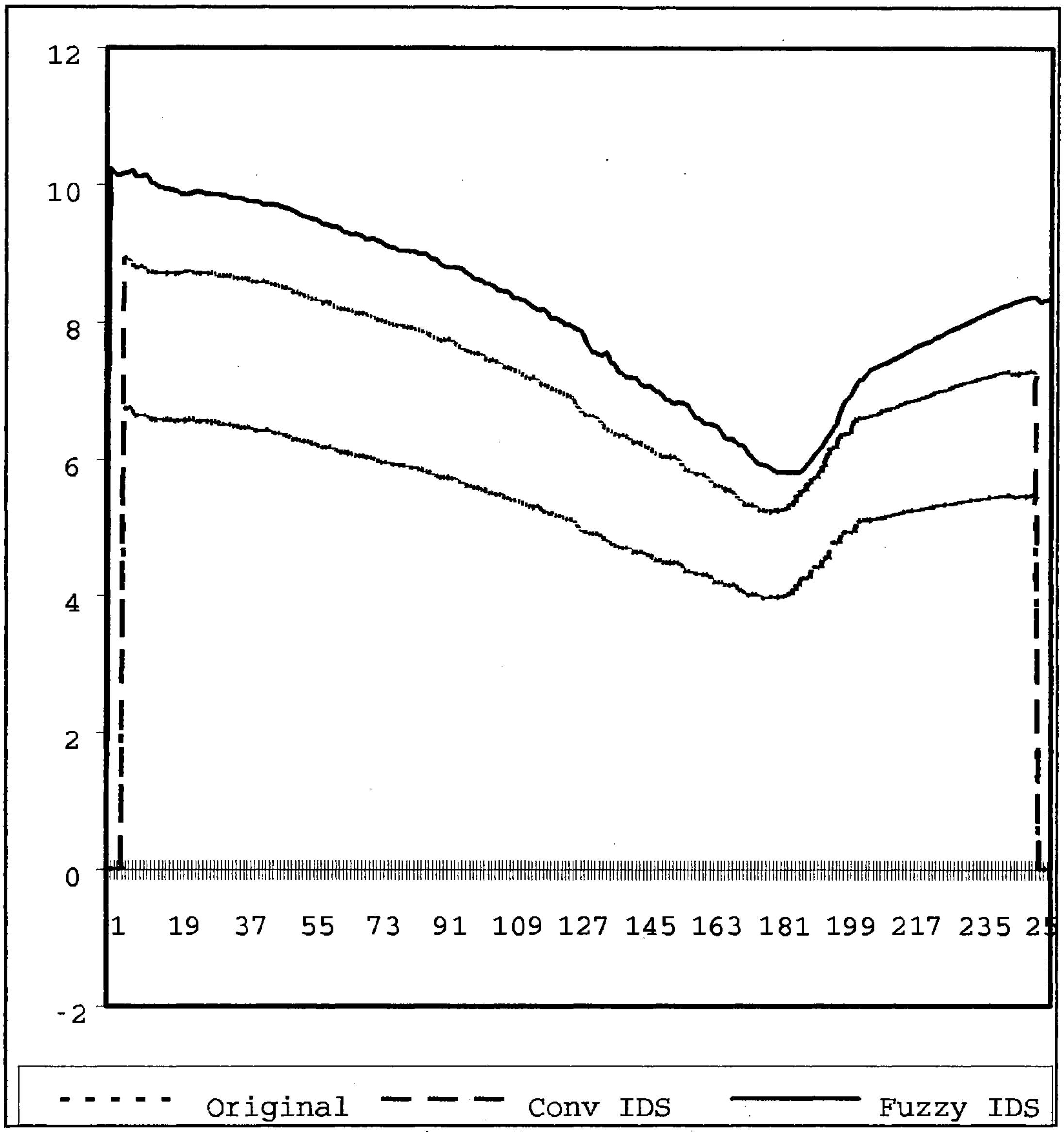



Fig V-6: COUPLE


12
10
8
6
4
2
0
-2
1 19 37 55 73 91 109 127 145 163 181 199 217 235 2
Original
Conv IDS
Fuzzy IDS
Fig V-7: GIRL

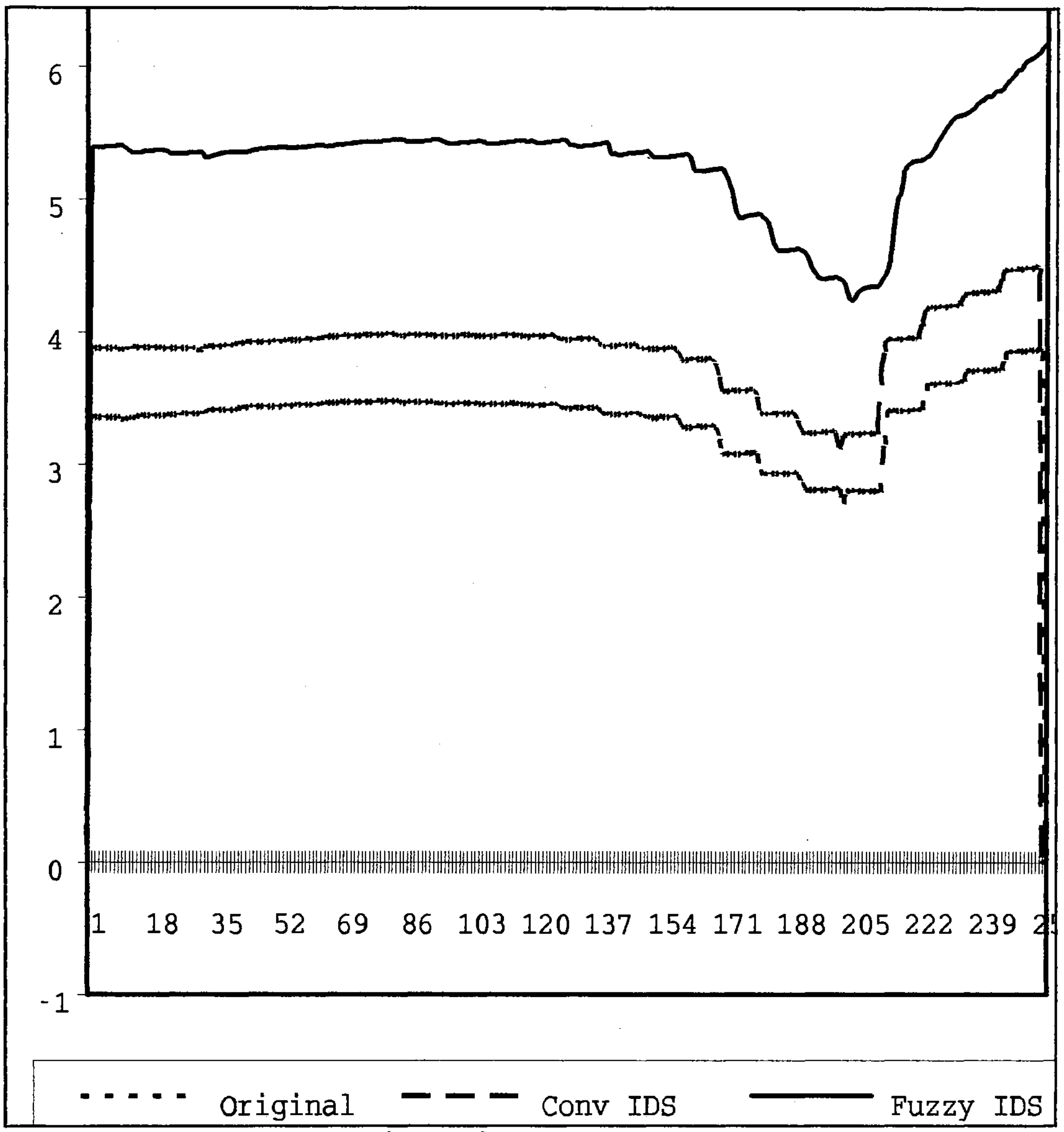


Fig V-8: GOLDNGAT

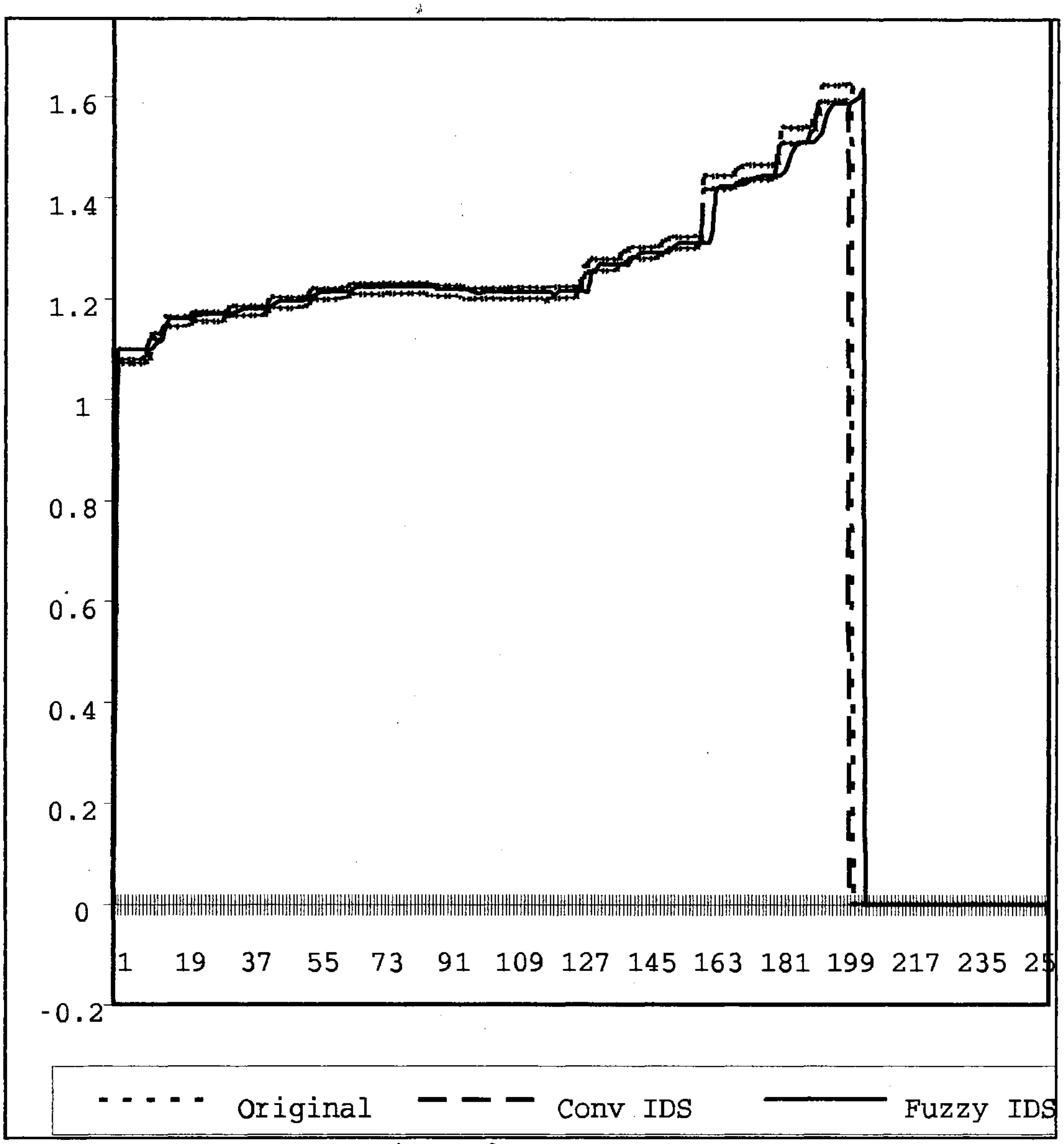



Fig V-9: JUPITER

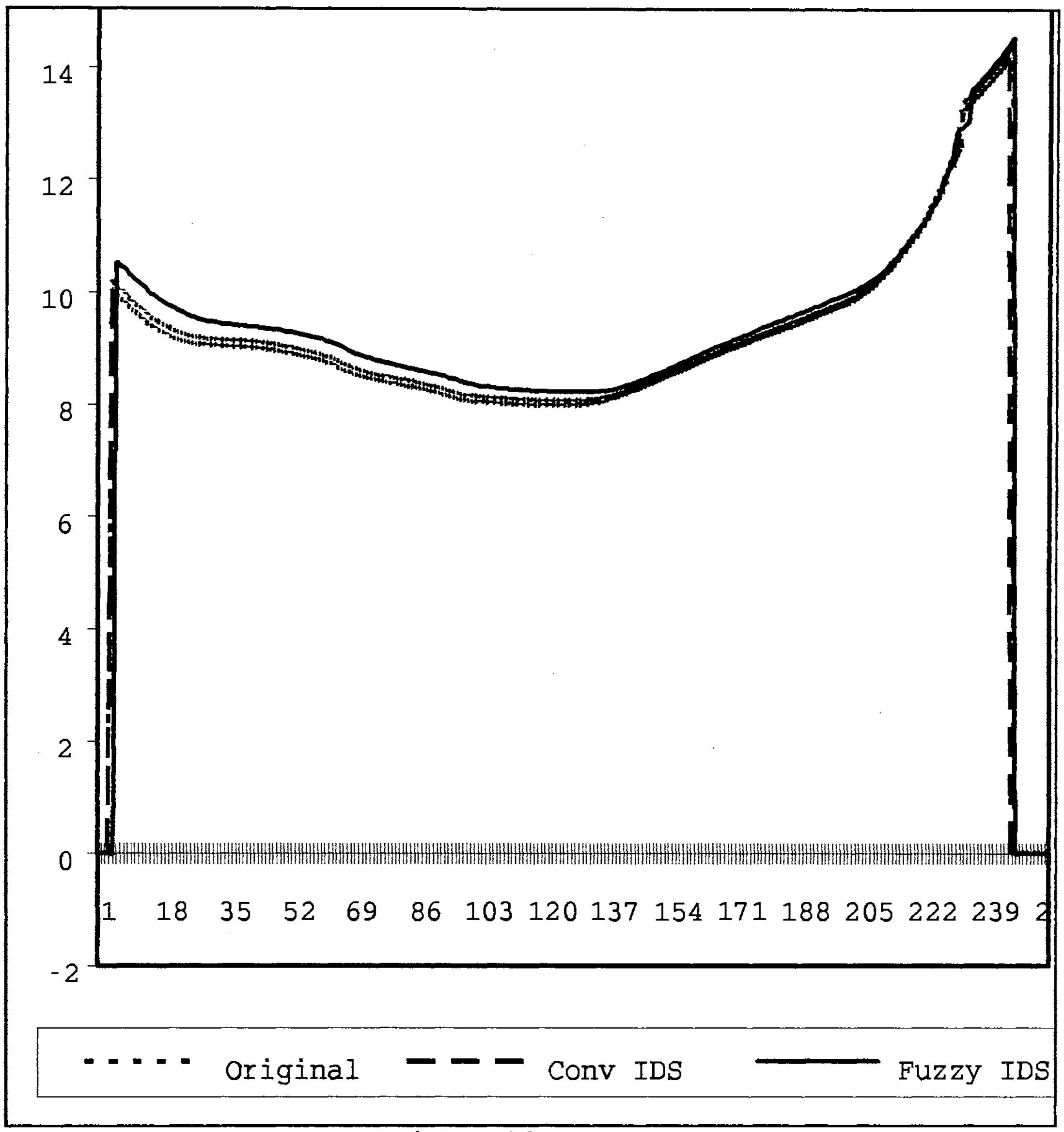

14
12
10
8
6
4
2
0
-2
1 18 35 52 69 86 103 120 137 154 171 188 205 222 239 2
Original
Conv IDS
Fuzzy IDS

Fig V-10: LENA

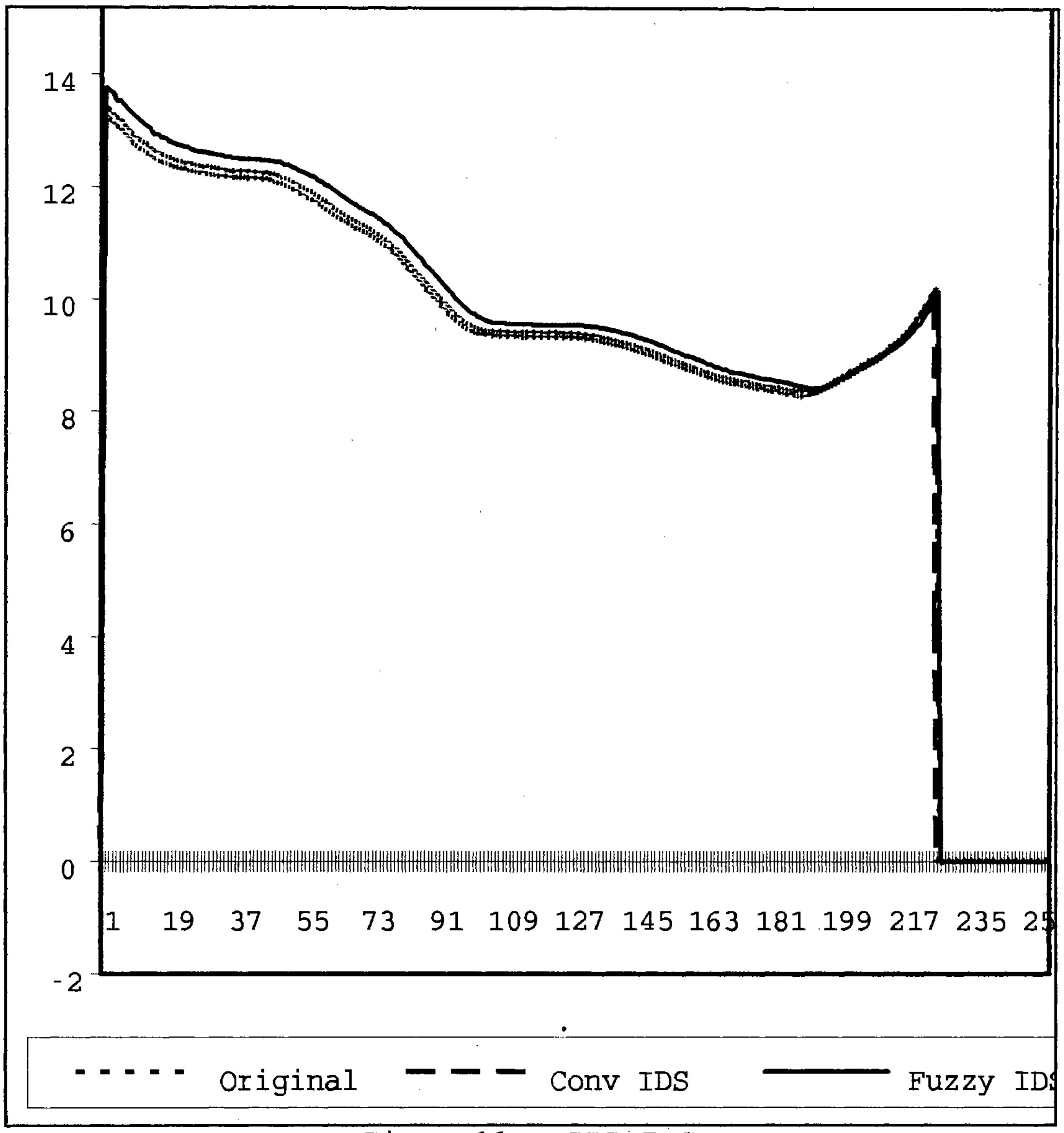


Fig V-11: PEPPERS

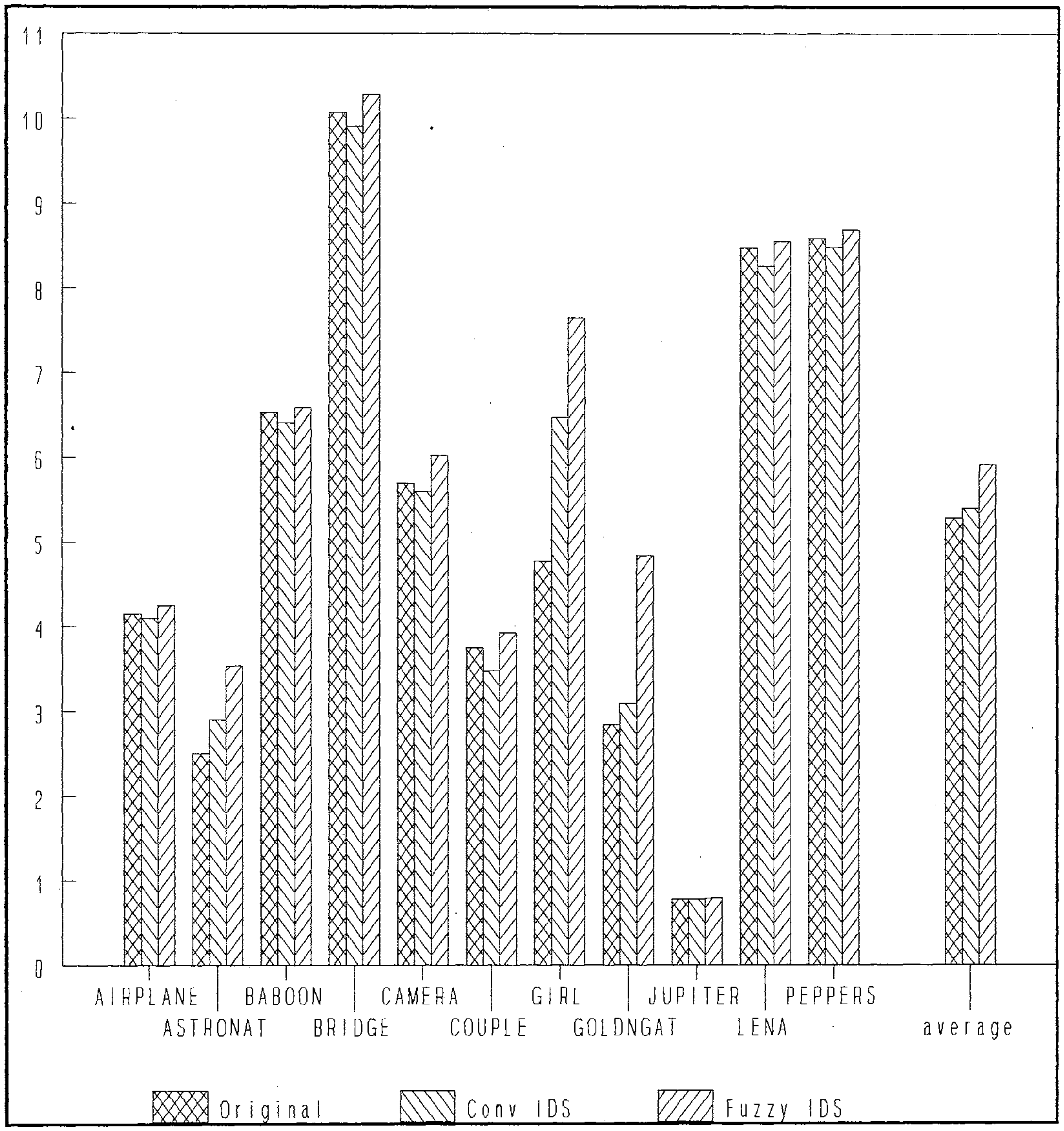
## APPENDIX VI-a

### AVERAGE BIMODALITY ANALYSIS
(numerical form)

| | *Original* | *Conventional IDS* | *Fuzzy IDS* |
|---|---|---|---|
| | ----------- | ----------------- | ----------- |
| AIRPLANE | 4.148438 | 4.101562 | 4.246094 |
| ASTRONAT | 2.503906 | 2.898438 | 3.531250 |
| BABOON | 6.527344 | 6.410156 | 6.582031 |
| BRIDGE | 10.066406 | 9.906250 | 10.281250 |
| CAMERA | 5.687500 | 5.593750 | 6.019531 |
| COUPLE | 3.750000 | 3.472656 | 3.925781 |
| GIRL | 4.769531 | 6.464844 | 7.652344 |
| GOLDNGAT | 2.847656 | 3.089844 | 4.835938 |
| JUPITER | 0.785156 | 0.781250 | 0.796875 |
| LENA | 8.476562 | 8.261719 | 8.554688 |
| PEPPERS | 8.582031 | 8.484375 | 8.691406 |
| average | 5.285866 | 5.405895 | 5.919744 |

APPENDIX VI-b

AVERAGE BIMODALITY ANALYSIS
(graphical form)



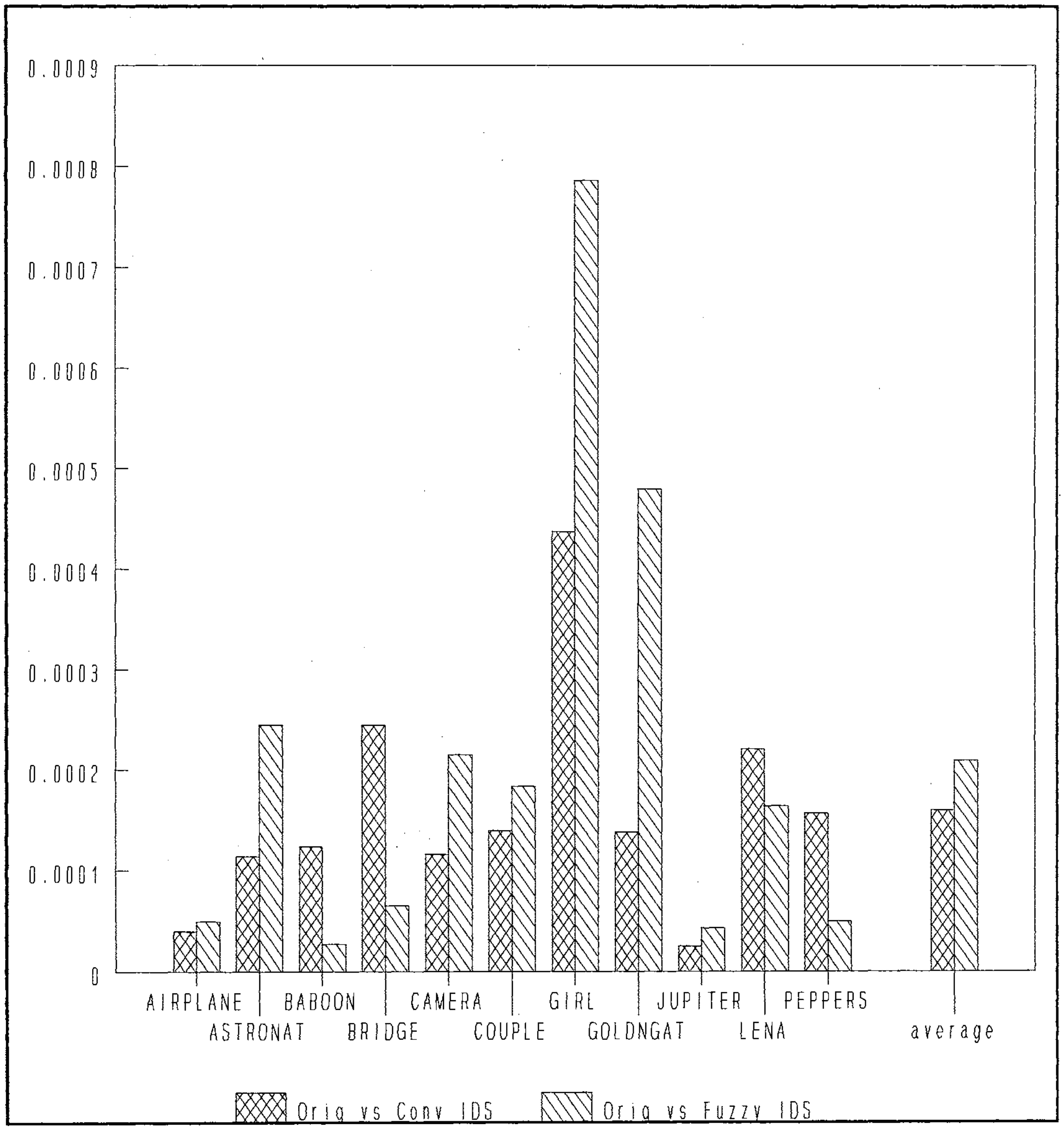
## APPENDIX VII-a

## ERMS ANALYSIS OF BIMODALITY
(numerical form)

| | *Original vs Conv IDS* | *Original vs Fuzzy IDS* |
|---|---|---|
| AIRPLANE | 0.000040 | 0.000050 |
| ASTRONAT | 0.000114 | 0.000245 |
| BABOON | 0.000124 | 0.000027 |
| BRIDGE | 0.000245 | 0.000065 |
| CAMERA | 0.000116 | 0.000215 |
| COUPLE | 0.000140 | 0.000184 |
| GIRL | 0.000437 | 0.000786 |
| GOLDNGAT | 0.000138 | 0.000479 |
| JUPITER | 0.000025 | 0.000043 |
| LENA | 0.000221 | 0.000164 |
| PEPPERS | 0.000157 | 0.000050 |
| average | 0.000160 | 0.000210 |

APPENDIX VII-b

ERMS ANALYSIS OF BIMODALITY
(graphical form)



# SPECIAL CASES

GREY-LEVEL REDUCTION

&

IMAGE SMOOTHING

APPENDIX VIII

SPECIAL CASE -- REDUCED GREY LEVELS

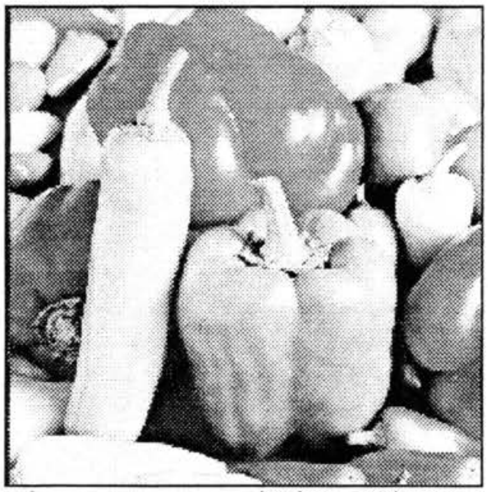


Fig VIII-a:original image

Fig-VIII-b: image with reduced grey levels

Fig VIII-c: IDS enhanced for reduced grey levels

Fig VIII-d:Fuzzy enhanced for reduced grey levels

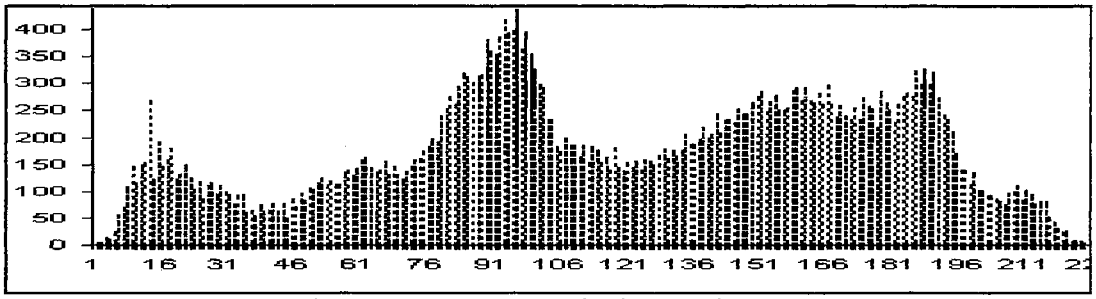



Fig VIII-1: original image

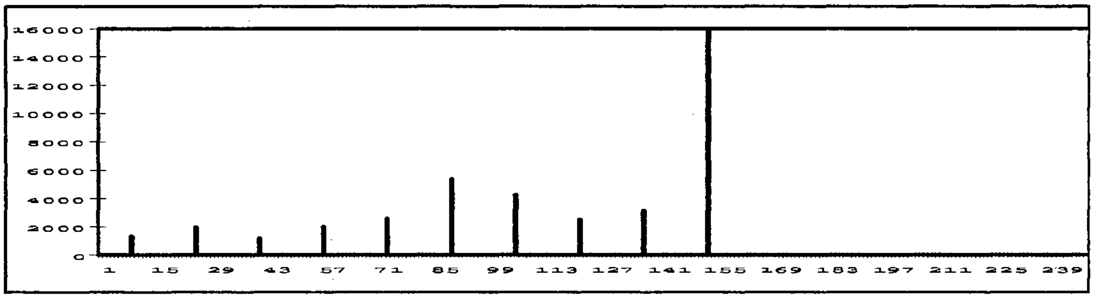



Fig VIII-2: reduced grey levels

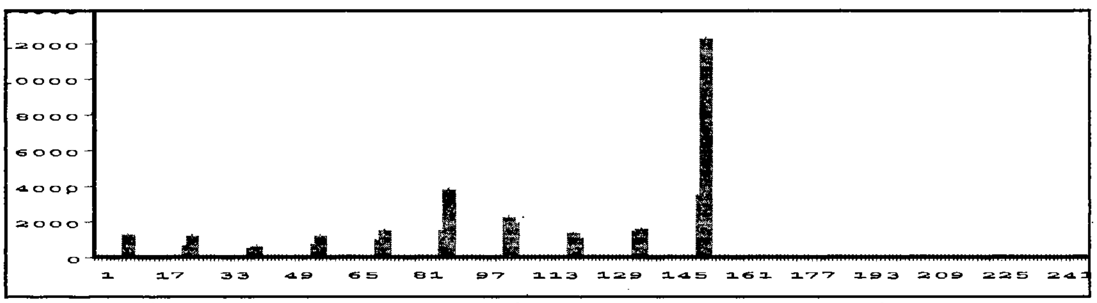



Fig VIII-3: Conventional IDS enhanced image
with reduced grey levels

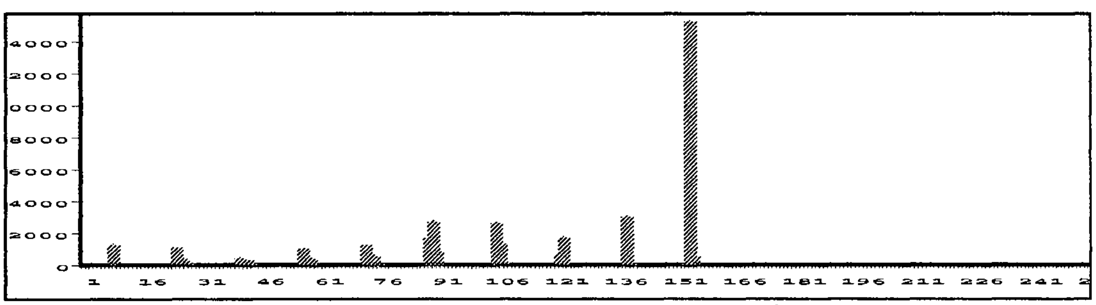



Fig VIII-4: Fuzzy enhanced image
with reduced grey levels

APPENDIX IX

SPECIAL CASE -- SMOOTHED IMAGE

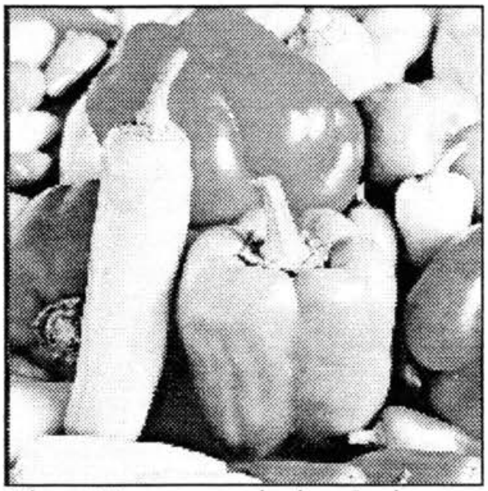


Fig IX-a: original image

Fig IX-b: Smoothed image

Fig IX-c: conventional enhanced smoothed image

Fig IX-d: Fuzzy enhanced smoothed image

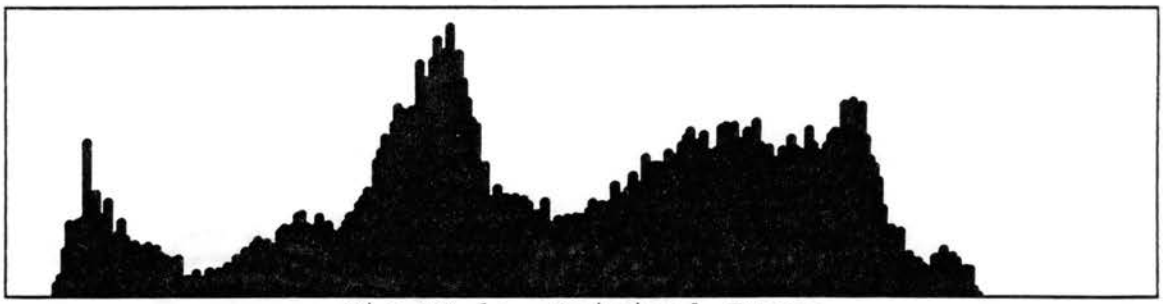


Fig IX-1: Original Image

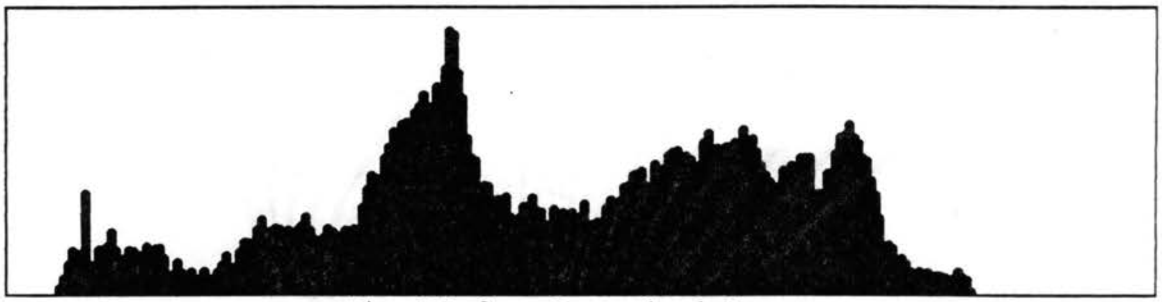


Fig IX-2: Smoothed Image

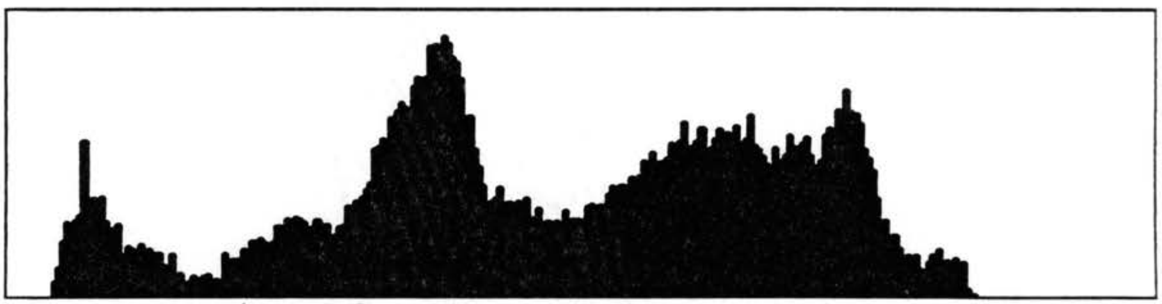


Fig IX-3: IDS Enhanced Smoothed Image

Fig IX-4: Fuzzy Enhanced Smoothed Image

VITA 2

Faisel Saeed

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Doctor of Philosophy

Thesis: A FUZZY IDS MODEL FOR IMAGE ENHANCEMENT

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