# Identification of Critical Errors in Imaging Applications*

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## Abstract

*Practical on-line test methods do not cover all possible faults of a system. We propose a method to identify critical faults and distinguish them from non-critical ones. Low-cost on-line fault detection can focus on the critical faults. Alternatively, the circuit sites associated with critical faults could be selectively hardened to improve the overall reliability of a system. This is done in a cost-effective way because no hardening against non-critical faults is required. In this work, we concentrate on faults in imaging applications such as video. We classify faults based on their impact on the system behavior, i.e., the visibility of their effects by a human end-user. The psychovisual model from the JPEG compression method is used for fault effect classification.*

**Keywords:** Low-cost on-line test, Selective hardening, Imaging applications, Error tolerance

## 1 Introduction

On-line fault detection is essential for integrated circuits manufactured in nanoscale technologies to handle the effects of radiation-induced soft errors, reliability failures, and non-trivial signal integrity conditions missed in manufacturing test. However, high coverage of potential faults is not achievable at acceptable costs. Many on-line detection architectures allow to select a (small) number of faults to be detected.

In this work, we suggest to use the *fault severity* information to select critical faults to be covered by the on-line detection. Fault severity is defined with respect to the application of the system. In this paper we concentrate on imaging applications such as image compression or video. We consider a fault to be severe if the human end-user observing the image produced by the faulty hardware would notice a difference to the image produced by the fault-free hardware. The calculation of fault severity is based on the psychovisual model used in JPEG compression [1]. JPEG (and other lossy compression schemes) achieve high compression rates by identifying the information in an image which is 'unimportant' for the human eye and compressing only the 'important' information. A hardware fault that leads to an image which deviates from the reference image (produced by fault-free hardware) only in an 'unimportant' way has a low severity. Intuitively, compressing the image produced by fault-free hardware and one produced by hardware with a low-severity fault would yield the same result.

Fault severity information is also useful for selective hardening of a circuit against soft errors [2] and for error-tolerant design [3, 4] (increasing yield by delivering defective hardware to the customer as long as the fault is shown to be tolerable, i.e., to result in *acceptable operation* of the system which contains the circuit as a component).

A simple measure for error tolerance is *threshold testing* [5]: A circuit is assumed to calculate a numerical value. A fault is considered tolerable if the difference between the value calculated by the faulty and the fault-free circuit is less than a pre-defined threshold.

## 2 Critical Error Identification

We first summarize the JPEG compression method which is the foundation of our psychovisual model, then the application of the model to images produced by a faulty circuit is discussed. A fault is considered severe if the differences between the images produced by the faulty and the fault-free circuit are not restricted to the 'perceptually unimportant' information as defined by the psychovisual model. Since JPEG supports different degrees of quality, the severity of a fault can be defined by the 'degree of its perceptability'.

The JPEG compression method partitions an image into blocks, applies the Discrete Cosine Transform (DCT) to the pixel values in the block, performs the *quantization* of the resulting values and applies lossless compression to its outcome. Quantization is the only step in which information loss occurs. The extent of the loss is determined by values in the *quantization matrix* $Q$: the larger the values, the more information is lost (and the better compression is achieved). The values in $Q$ are selected such as to reflect the significance of the image data component (after DCT) for the human eye. Hence, $Q$ is called the *psychovisual model*. Such a model can be derived from medical experiments or analytically.

The psychovisual model $Q$ can be applied to decide whether a human observer would distinguish between an image $I$ produced by a fault-free circuit and an image $I^f$ produced by a circuit affected by a fault $f$. DCT and quan-

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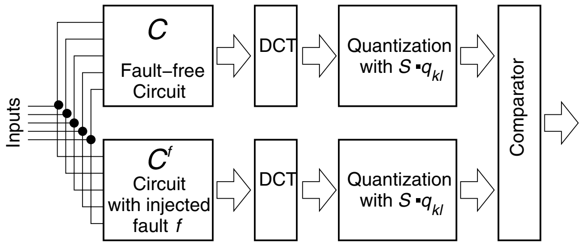


Figure 1: Determining of severity $S$ of a fault $f$ using the psychovisual model

tization using $Q$ is run on both images. If identical results are obtained for both images, then there is no visible difference between the two images even though their actual pixel values may differ.

To allow perceptible, yet limited image deviations. $Q$ is multiplied by an integer $S$. We define the *psychovisual extent of deviation* (PED) of two images as the lowest $S$ for which the quantization of both images with quantization matrix $S \cdot Q$ yields identical results.

The definition above assumes a circuit which produces only one image $I$. However, circuits generally produce multiple images, and they depend on its starting state and input vectors. The *worst-case severity* for fault $f$ denotes the maximal possible PED of $f$ and $I^f$ for any input sequence. The *average-case severity* is the PED of $I$ and $I^f$ averaged for all input sequences.

# 3 Experimental Results

We implemented the circuit from Figure 1 for JPEG's default $Q$ and different values of $S$ in VHDL. Unfortunately, we currently have no access to benchmark circuits from image processing domain. As a consequence, we generated our own circuits for use as preliminary benchmarks from images aerial, airplane, chart, clock, moon and plant from the USC-SIPI Image Database (`http://sipi.usc.edu/database/`). For each of these images we designed a circuit which has neither inputs nor memory elements and constantly holds the pixel information of the respective image on its outputs. We used the bit-flip fault model. Since all reference images consisted of 65,536 pixels and 8 bits are used to store a pixel, there were 524,288 faults per circuit.

We determined the severity of each fault as the smallest value of the integer $S$ such that the images produced by the fault-free and the faulty circuits do not differ after quantization by $S \cdot Q$. The percentages of faults with severity 1 through 16 are shown in Table 1. Its last row aggregates all faults with severity exceeding 16. Most faults have a relatively low severity. The percentage of severe faults tends to be higher for aerial and plant. This is due to a higher *activity* of these images, i.e., many sudden changes in luminance. If faults with severity 4 are acceptable, then only 15% and 28% of the faults must be covered by on-line detection or selectively hardened for circuits airplane and plant, respectively.

| $S$ | aerial | airplane | chart | clock | moon | plant |
|---|---|---|---|---|---|---|
| 1 | 26.86 | 40.02 | 28.57 | 39.21 | 28.73 | 27.72 |
| 2 | 19.50 | 23.13 | 39.68 | 22.28 | 22.73 | 20.87 |
| 3 | 11.44 | 13.23 | 9.21 | 13.05 | 14.70 | 12.52 |
| 4 | 10.48 | 8.87 | 7.08 | 8.47 | 11.18 | 10.49 |
| 5 | 7.24 | 5.94 | 6.10 | 6.46 | 8.15 | 7.43 |
| 6 | 5.95 | 4.45 | 2.21 | 3.71 | 5.50 | 5.73 |
| 7 | 4.56 | 1.97 | 2.26 | 2.24 | 3.62 | 4.45 |
| 8 | 3.65 | 0.91 | 1.36 | 1.39 | 2.26 | 3.29 |
| 9 | 2.84 | 0.52 | 0.92 | 1.02 | 1.34 | 2.44 |
| 10 | 2.25 | 0.31 | 0.71 | 0.74 | 0.73 | 1.65 |
| 11 | 1.60 | 0.23 | 0.48 | 0.52 | 0.42 | 1.17 |
| 12 | 1.21 | 0.12 | 0.42 | 0.32 | 0.28 | 0.80 |
| 13 | 0.81 | 0.12 | 0.29 | 0.21 | 0.18 | 0.52 |
| 14 | 0.53 | 0.08 | 0.21 | 0.13 | 0.09 | 0.32 |
| 15 | 0.40 | 0.04 | 0.14 | 0.09 | 0.04 | 0.23 |
| 16 | 0.25 | 0.02 | 0.11 | 0.07 | 0.03 | 0.13 |
| >16 | 0.41 | 0.04 | 0.25 | 0.10 | 0.02 | 0.22 |

Table 1: Fault severity (in per cent) in benchmarks generated from images

We also generated data for faults on specific bits (the results are omitted due to space restrictions). The results show that the faults on lower bits tend to have a smaller severity. However this is not valid universally. Consequently, the simpler threshold testing [5] does not always achieve the accuracy of the proposed psychovisual model.

# 4 Conclusions

We proposed the concept of *fault severity* which allows an automatic and systematic identification of such faults. In addition to covering severe faults by on-line detection, their sites in the circuit can undergo selective hardening. Fault severity information can be used in combination with fault occurrence probability data which have been obtained by other authors. We described a model of fault severity in imaging applications based on human perception. Preliminary results indicate that a significant number of faults can be excluded from consideration if limited image deviations are acceptable. Existing simple metrics turn out to be less accurate than the introduced model. Our next goal for the future is to obtain actual image-processing circuits and to apply the fault severity identification method to that circuits.

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