Genetic Algorithm Optimization of Multidimensional Grayscale Soft Morphological Filters With Applications in Film Archive Restoration

Mahmoud S. Hamid, Neal R. Harvey, and Stephen Marshall

Abstract—Automatic restoration of old film archives has become of increasing interest in the last few years with the rise of consumer digital video applications and the need to supply more programming material of an acceptable quality in a multimedia context. A technique is described for the optimization of multidimensional grayscale soft morphological filters for applications in automatic film archive restoration, specific to the problem of film dirt removal. The optimization is undertaken with respect to a criterion based on mean absolute error and is performed using a genetic algorithm. Experiments have shown that the filter found using this technique has excellent performance in attenuating/removing film dirt from image sequences and has little, if any, effect on the image detail. The results of applying such a filter to a real image sequence were analyzed and compared to those obtained by restoring the same image sequence using a global filtering approach (LUM filter) and a spatio-temporal local filtering approach (ML3Dex filter with noise detection). From a film dirt removal point of view, the optimized soft morphological filter showed improved results compared to the LUM filter and comparable results with respect to the ML3Dex filter with noise detection. Also, the optimized filter accurately restored all fast-moving objects present in the sequence, without the need for motion compensation, whereas the other two methods failed to do this. The proposed method proved to be a simple, fast, and cheap approach for the automatic restoration of old film archives.

Index Terms—Film restoration, filter optimization, genetic algorithms, soft morphology.

I. INTRODUCTION

T HERE HAS BEEN growing interest in recent years in the area of film archive restoration. This has, no doubt, come about in part due to the emergence of digital television broad-casting and the growth in video and DVD sales. In order to satisfy demand, it is becoming increasingly attractive to market available archive material. However, a great deal of film archive material has suffered some form of corruption and therefore requires restoration in order to be of a sufficient quality for resale or broadcast. This paper describes a method whereby grayscale soft morphological filters may be optimized with respect to a specific objective image quality criterion, and its application

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in addressing a particular problem in film archive restoration, known as film dirt.

Film dirt is a common problem in old film archives and will be familiar to anyone who has been to the cinema or viewed old film footage. Film dirt occurs when foreign particles get caught in the film transport mechanism and damage the film, causing loss of information. This damage manifests itself as "blotches" of random size, shape and intensity. The blotches appear as flashes of dark and bright patches called dirt and sparkle. Dirt is created when dust adheres to the film as it passes through the transport mechanism, while sparkle is caused by the abrasion of the film emulsion. These blotches are nontime correlated (temporally impulsive).

Later in their lifetime, films may suffer further damage due to environmental hazards such as humidity and dust, chemical instabilities, improper storage and handling practices, and even poorly maintained projectors. Although the deterioration of film sequences can be halted and movies can be preserved by the production of master video copies, defects already present in the film are inherited in the video and, in fact, most defects are actually accentuated in the viewing of video in comparison to film. Also, additional artifacts may be embedded in the videotape due to the film to video transfer operation.

Whatever the case, the complexity and associated cost of manual processes involved in a conventional restoration chain are often too prohibitive for a successful exploitation business plan to emerge. Additionally, conventional restoration of film archives relies on the use of dedicated equipment such as special copying machines, which can only target a limited range of artifacts due to the fact that the unit of manipulation can only be the physical film strip. For all these reasons, it became necessary to digitize movies and apply the restoration techniques in this domain for them to be of acceptable quality for resale or broadcast.

There is growing consensus that automatic restoration is a key enabling technology toward the successful exploitation of film and television archives for a number of reasons. By improving baseline picture quality and reducing the perceptual impact of archive-related artifacts, it can meet viewers' aesthetic expectations and enrich the viewing experience. Moreover, the suppression of such artifacts has vital implications on the efficiency of video-coding algorithms used in the television and multimedia distribution chains, such as MPEG-2 and MPEG-4.

In contrast to classical image sequence restoration methods, an automatic digital film restoration system, for example [1], [2], should work under the following constraints:

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Old films must be scanned at high resolutions in order to preserve the definition and the visual quality of the motion picture images. Consequently, the restoration algorithms must also preserve the visual quality of the films. In addition, the restoration process should be as fast as possible, have the minimum number of control parameters, and the processing system has to be cheap.

Most of the conventional image sequence restoration algorithms involve median filtering [4]. Although the median filter better preserves edges than linear filters, the median operation tends to homogenize the details of the image and this results in a blurring effect. In fact, the median applies the same filtering operation regardless of the underlying statistics of either the image or the noise. It is, therefore, highly unlikely that the median would be the optimum processing function in any given situation. It would almost always be possible to improve on its performance.

To enable greater fidelity to be achieved in the image sequence, Nieminen introduced the multilevel median filter (MMF) [6]. This class of filters employs a hierarchy of median operations that allows one to reject impulsive distortions in the image with less smoothing than a simple median operation. Extended versions of MMF filter have been proposed by Arce [7] and Alp [8].

One of the most difficult aspects of film restoration involves the way in which motion is handled. Estimation of motion from image sequences is, in general, a difficult and time-consuming task. It is also difficult to have an idea of the real sensitivity to noise or to image alteration of a motion estimator. Let us emphasize that spatio-temporal restoration algorithms are more effective than two-dimensional (2-D) (purely spatial) processes only if the motion estimator performs satisfactorily. However, the behavior of a motion estimator cannot be guaranteed. There is also the consideration that the sequences being dealt with are degraded, so the motion estimator must be robust to noise. Furthermore, three-dimensional (3-D) (spatio-temporal) restoration methods are far more computationally expensive than 2-D techniques.

The topological median filter [5] is a recently introduced type of median filter for images. It implements some existing ideas and some new ideas on fuzzy connectedness to improve the extraction of edges in noise over a conventional median filter. Although the results of applying this filter to images show a better performance than the median filter in preserving edges, the filter fails to perfectly restore small details in the images. This makes the visual quality of the filtered images [5] unacceptable for many multimedia applications.

The majority of existing methods, for example [3], [9], and [10], involve a "detect and repair" strategy, in which artifacts are detected and then filtering is applied only at those places where artifacts have been detected. They also employ motion compensation. As will be seen later, in the cases where motion is rotational or where it exceeds the Nyquist sampling rate of the frames, it is difficult to make the motion compensation sufficiently robust. In contrast, the method introduced in this paper seeks to determine the optimal filter subject to certain constraints. Given some region of support, the operator that minimizes the difference between a filtered version of a corrupted

image and an ideal image is determined. An eventual practical tool based on this method would be virtually automatic, requiring little human interaction and would have no manually set parameters. In any case, it would have determined the optimum filtering function achievable via soft morphological filtering, or at least a function very close to it for the given training set. It is therefore unlikely that human intervention could improve the result further.

The method is based on a global filtering approach in which a soft morphological filter is optimized using a genetic algorithm (GA). The filter found is then used to restore a corrupted film sequence. The proposed restoration method automatically detects, and then corrects, artifacts in degraded motion pictures with minimal human intervention, as it has no control parameters.

GAs [11], [12] have proven to be a good tool for optimization and search and have found applications in many areas of science and engineering in recent years. The exhaustive processing required is the main drawback of using GAs in optimization problems whenever both the search space and the amount of data to be processed are large. Recently, this has become less of an obstacle after the emergence of parallel GAs [13]–[15] and the implementation of GA design approaches on field-programmable gate arrays (FPGA) [16]. A parallel implementation method for reducing the processing time of the GA using an FPGA, specific to the problem of film restoration, showed a massive reduction in the optimization time. A publication on this work is in preparation by the authors.

The results of applying the proposed method to a real corrupted film sequence was analyzed and compared to those obtained by applying two other filtering approaches to the same film sequence. The first approach is a global filtering approach in which the LUM filter [17], [18] was used. The second approach is a spatio-temporal local filtering method in which the ML3Dex filter, proposed by Kokaram [20], was used after the detection of the noise using the ROD detector [19].

The remainder of the paper is organized as follows. Section II provides an introduction to the class of soft morphological filters. Section III explains the idea behind restoring film sequences using spatio-temporal soft morphological filters. Section IV describes how GAs can be used in the search for optimal grayscale soft morphological filter parameters. Section V demonstrates the application of the optimization method to the film dirt problem. Section VI shows the results of applying the technique to some real restoration tasks and compares the results with those obtained by applying two other filtering methods to the same image sequence. Section VII discusses the results presented in Section VII. A summary and conclusion are presented in Section VIII.

II. SOFT MORPHOLOGICAL FILTERS

Here, we provide an overview of grayscale soft morphological filters. In the interest of brevity, we restrict ourselves to grayscale (function processing) soft morphological filters and have omitted the description and definition of flat (function-setprocessing) and binary (set processing) soft morphological filters. For this, the interested reader is referred to [23]. The restriction to grayscale (function processing) soft morphological filters is justifiable as the classes of flat (function-set-processing) and binary (set processing) soft morphological filters are subsets of the class of grayscale soft morphological filters.

Soft morphological filters are a class of nonlinear filters [22]-[24]. Their definition was originally related to the class of (standard/structural) morphological filters (discrete flat morphological filters), but they have since been extended to the grayscale (function processing) case [21]. The idea behind soft morphological filters is to relax the standard definitions of morphological filters in such a way as to achieve robustness whilst retaining most of the desirable properties of standard morphological filters. Whereas standard morphological filters are based on local maximum and minimum operations, in soft morphological filters these operations are replaced by more general weighted order statistics. The key idea of soft morphological operations is that the structuring element is divided into two parts: the hard center which behaves like the standard structuring element and the soft boundary, where maximum and minimum are replaced by other order statistics. This makes the filters behave less rigidly in noisy conditions and makes them more tolerant to small variations in the shapes of the objects in the filtered image. Before proceeding to the definitions of the soft morphological operations, some other concepts need to be defined.

The structuring system [b, a, r] consists of three parameters: functions a and b, having support A and B respectively $(A \subseteq B)$ and a natural number, r, satisfying $1 \leq r \leq |B|$, where |B| is the cardinality of B. Function b is called the structuring function, a is its (hard) center (A is the support of its hard center), $b \setminus a$ its soft boundary ($B \setminus A$, the support of its soft boundary), and r is the order index of its center which is also referred to as the repetition parameter.

Grayscale soft dilation of a signal f by the structuring system [b, a, r] is denoted by, $f \oplus [b, a, r]$ and is defined as

$$f \oplus [b, a, r](x) = \text{the } r^{\text{th}} \text{ largest value of the multiset} \{r \diamond (f(x - \alpha) + a(\alpha))\} \cup \{f(x - \beta) + b(\beta)\}$$
(1)

where $\alpha \in A$ and $\beta \in B \setminus A$ and the symbol \diamond is used to denote duplication; for instance

$$n \diamond x = \overbrace{x, \dots, x}^{n \ times}.$$
 (2)

Grayscale soft erosion of a signal f by the structuring system [b, a, r] is denoted by $f \ominus [b, a, r]$ and is defined as

$$f \ominus [b, a, r](x) = \text{the } r^{\text{th}} \text{ smallest value of the multiset} \{r \diamond (f(x - \alpha) - a(\alpha))\} \cup \{f(x - \beta) - b(\beta)\}$$
(3)

where $\alpha \in A$ and $\beta \in B \setminus A$.

As an extreme case, grayscale soft morphological operations by the structuring system [b, a, r] reduce to the equivalent grayscale standard morphological operations by the function bif r = 1, or, alternatively if $A \equiv B$. If $r > |B \setminus A|$, grayscale soft morphological operations by the structuring system [b, a, r] reduce to the equivalent grayscale standard morphological operations by the structuring function a.

Grayscale soft opening of f by [b, a, r] is denoted by $f_{[b,a,r]}$ and is defined as

$$f_{[b,a,r]}(x) = (f \ominus [b,a,r]) \oplus [b^s, a^s, r](x).$$
(4)

Grayscale soft closing of f by [b, a, r] is denoted by $f^{[b,a,r]}$ and is defined as

$$f^{[b,a,r]}(x) = (f \oplus [b,a,r]) \ominus [b^s, a^s, r](x).$$
(5)

Note that, the symmetric set of T is the set

$$T^{s} = \{-t : t \in T\}.$$
(6)

Grayscale soft open-closing and soft close-opening are combinations of the soft closing and soft opening operations shown above.

Kuosmanen [25] showed that, unlike standard closing and opening, soft closing and soft opening by the structuring system [b, a, r], where a is symmetric, can remove arbitrary shaped positive and negative impulses, if

$$|C| \le \min\left\{\frac{|b|-r}{|a|}, r-1\right\}$$
(7)

where |C| is the cardinality of the impulsive noise.

The cardinality of the noise is related to its density and corresponds to the number of pixels in the set C. These noisy pixels are within the region of support of the SMF.

III. WHY EXTEND TO THE SPATIO-TEMPORAL DOMAIN?

Basically, a video sequence is a much richer source of visual information than a still image; this is primarily due to the presence of motion. Because the recording of each image of a motion picture sequence generally occurs more rapidly than the change of information in the scene, the consecutive images in the sequence may contain similar or redundant information.

On the other hand, image sequences that contain fast motion, which exceeds the Nyquist sampling limit defined by the frame rate, have always been a problem in the restoration of film archives. This is because objects having this type of motion are very similar, in their temporal characteristics, to film dirt. So, it may not be possible to predict this type of motion from adjacent frames. For example, if an object only appears briefly in a single frame and not in adjacent frames, no prediction would be possible. Therefore, any suitable restoration algorithm should be able to distinguish between film dirt and these fast-moving objects; however, this adds more complexity to the algorithm.

Although the restoration of degraded image sequences can be performed with the repeated execution of the same 2-D process on the separate images in the sequence [28], [29], such an approach implicitly assumes that the individual images, or frames, are temporally independent and thus has a tendency to introduce temporal artifacts in the restored image sequence.

By extending the filtering process from purely spatial to spatio-temporal, it is anticipated that the resulting filters will make use of the temporal characteristics and in this way outperform their purely spatial counterparts. However, by careful coding of the filter parameters for GA optimization, the search space for spatio-temporal (3-D) filters will also include the filters of lesser dimensions, i.e., 2-D (purely spatial) and 1-D (purely temporal), and so the GA will be free to choose the optimal filter amongst them.

IV. OPTIMIZATION OF SMF USING GA

Several methods have been described for the optimization of soft morphological filters. Huttunen *et al.* [26] and Kuosmanen *et al.* [27] described methods for the optimal choice of the (2-D) flat (function-set-processing) soft morphological structuring system. These methods do not, however, optimize the choice of soft morphological operations. Harvey [29] described a method for the optimization of (2-D/spatial) grayscale soft morphological filters that seeks to optimize not only the structuring system, but also the choice of the soft morphological operations. In this paper we seek to illustrate the extension of these techniques to the optimization of grayscale soft morphological filters in the spatio-temporal domain and to illustrate their performance in the restoration of real corrupted image sequences.

GAs are a family of computational models based on the mechanics of evolution and genetics, which may be used in the solution of search and optimization problems. The field of GAs was founded by John Holland [30]. Holland elaborated on two persistent themes of his research: the ability of simple data representations to encode complicated structures and the power of simple transformations to improve such structures. He showed that, with the right control structure, these simple data representations (strings) could attain rapid improvements under certain transformations, so that a population of the strings could be made to evolve in a manner similar to that of naturally occurring populations. In their simplest form, three basic operators, reproduction, crossover, and mutation, act on a population of candidate solutions (chromosomes) in the search space.

- *Reproduction:* a process whereby individual chromosomes are selected according to their fitness values.
- Crossover: a recombination operator that combines segments from two parent chromosomes to produce offspring. These segments are called genes. The values of the genes are so-called alleles. As in the natural system, the offspring contain genes from the two parent chromosomes. A probability term P_c is set to determine the crossover rate.
- *Mutation:* an operator that introduces variations into the chromosome. A probability term P_m is set to determine the mutation rate. Practically, crossover is used for the exploitation of the chromosomes with good genetic material while mutation is performed to create a random diversity in the population, or in other words for the exploration of the entire search space.

A. Soft Morphological Filter Parameters

In searching for the optimal soft morphological filter the following parameters have to be considered:

- *size* and *shape* of the structuring system's hard center;
- *size* and *shape* of the structuring system's soft boundary; *repetition* parameter;
- choice of the soft morphological operations.

TABLE I EXAMPLE OF CODE FOR CODING POSITIONS WITHIN AND OUTSIDE THE OVERALL STRUCTURING FUNCTION'S SUPPORT

Code	Grayscale Value
0	*
1	0
2	1
3	2
4	3
5	4

These parameters are incorporated into a GA optimization strategy. The parameters are encoded and mapped to a "chromosome," as described below.

1) Overall Structuring Function: Limits as to the dimensions of the overall structuring functions are set (i.e., the spatial, temporal, and grayscale dimensions) and the optimization process is allowed to search for any size and shape of the overall structuring function within this 4-D hypercube "envelope." If the overall spatio-temporal dimensions of the structuring function are fixed, it may be that, for a particular structuring function, not all positions within this region are in the actual support. In order to take this into account in the GA optimization process, it is necessary for positions outside the structuring function's support but within the overall search envelope ("don't care" positions) to be distinguishable. A suitable code, therefore, would be one, which includes a unique representation for those "null" positions. An example of such an encoding scheme is shown in Table I. In this example, "*" refers to a position outside the structuring function's support.

a) Hard Center: A binary string, having a length equivalent to the cardinality of the structuring function's overall support "envelope," is used to flag those positions within the structuring function's support which are in the hard center. Positions in this string with value one are positions within the structuring function that are included in the hard center. After forming each new individual, the hard center flags are checked against the structuring function portion of the chromosome. If any of the positions within the structuring function portion of support, i.e., "null" positions, then a check is made to ensure that the corresponding position within the hard center flag string has a zero and is changed as necessary.

b) Soft Boundary: Chromosome positions within the overall structuring function's support not coded as null positions and not having a one in the corresponding hard center flag portion of the chromosome are considered to be in the soft boundary of the structuring function.

2) Repetition Parameter: From the definition of soft morphological operations, it is known that for a structuring function, b having a support B, the repetition parameter r has to lie somewhere in the range $1 \le r \le |B|$. So, in order to code the repetition parameter, we can have a binary string, the length

Filter values bits	Structuring function bits	Rank bits	Soft morphological	operations bits
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Fig. 1. Chromosome coding.

of which is equal to the overall size of the structuring function (i.e., the pre-set outer limits of the structuring function's support). This binary string is then used to flag whether a position within the structuring function's support contributes to the repetition parameter; a one signifies that it does. To ensure consistency, a check has to be made, after forming each new individual, to confirm that those positions flagged as contributing to the repetition parameter are also positions coded as being within the structuring function's support. If any positions in the repetition parameter binary string are flagged with a one, but the corresponding positions in the structuring function's support are coded as being outside the structuring function's support, these flags have to be altered to ensure that they are set to zero. In this way the binary string can only code values lying within the allowable range.

3) Choice of the Sequence of Soft Morphological Operations: When considering soft morphological operations in the context of the design of soft morphological filters, one has to consider the search space within which the GA will operate. Here, we seek to limit our search to the set of fundamental (primary), secondary, and tertiary soft morphological operations, i.e., the set which includes {soft erosion, soft dilation, soft opening, soft closing, soft open-closing, and soft close-opening}. Each member of this set can be defined as some combination of the fundamental soft morphological operations. Therefore, for a coding scheme to be able to encode this set of soft morphological operations, two basic decisions have to be made.

- The set of individual soft morphological operators from which to choose.
- The maximum number of soft morphological operations in the sequence.

So, to be able to code the primary, secondary, and tertiary soft morphological operations, the set of soft morphological operators necessary is {soft erosion, soft dilation} and the sequence length required is four, i.e., the longest sequence of operations will be for the tertiary operations of soft open-closing and soft close-opening, which can be defined in terms of the fundamental (primary) operations as a sequence of four separate primary operations. In order that the GA be able to perform optimization over the entire search space, it is necessary to include the do-nothing, or identity operation, to the set of soft morphological operations. This is due to the fact that the length of the sequence of soft morphological operations is fixed in the GA, but it is desirable to include in the search space all the subsets of soft morphological operations from the simple soft erosion and soft dilation through the soft open-closing and soft close-opening filters.

B. Combining the Coded Structuring Function's Hard Center and Soft Boundary, Repetition Parameter, and Sequence of Soft Morphological Operations

To form the complete chromosome, the separate strings containing the coded structuring function, hard center and soft boundary, repetition parameter, and sequence of soft morphological operations are simply concatenated. This process of using the structuring function genes, as control genes, for controlling the genes of the filter hard center and soft boundary is referred to as the so-called hierarchical GA [12]. The chromosomal representation of the SMF is illustrated in Fig. 1.

The size of the search space is, therefore, fixed. The overall dimensions of the structuring functions-the maximum size of its support (and hence the support of the hard center and soft boundary and the range of possible repetition parameters), the maximum gray-level values, and the maximum length of soft morphological operations, together with the choice of soft morphological operations, are all set beforehand. Thus, the GA searches for any 3-D grayscale soft morphological filter which is a combination of four operations from the set {soft erode, soft dilate, do-nothing}, which will use a structuring function (hard center and soft boundary) and repetition parameter, chosen from all the possible variations within the overall region of support and maximum grey-level value. This search space encompasses (3-D) spatio-temporal, 2-D (purely spatial), and 1-D (purely temporal) soft morphological filters. In addition, the class of soft morphological filters encompasses several other classes of nonlinear filters including standard morphological filters and rank-order filters.

V. APPLYING THE GA OPTIMIZATION METHOD TO THE FILM DIRT PROBLEM

In order to make use of a GA in the optimization of filter parameters, there has to be some method of attributing a fitness value to an individual chromosome representing a particular set of grayscale soft morphological filter parameters. A fitness function has to be determined which provides some objective measure of the individual's performance in its environment. This fitness function is crucial to the successful implementation of the GA optimization technique. One then has to determine what is meant, in this application, by performance and environment. Defining the environment is a relatively simple matter. It is the image sequence to be filtered. Defining what is meant by performance, however, is a more complicated task. The general idea in the field of image restoration is that of improving the subjective quality of the images when viewed.

Unfortunately, due to the nature of the human visual system and its interaction with the human brain, there does not exist a simple function which maps subjective image quality to some objective quality criterion. This aspect itself forms a large area of research.

Criteria do exist, however, which provide some objective measure of image quality. The majority of these criteria are based on a comparison with an ideal (uncorrupted) version of the image under consideration which contains some modification of signal-to-noise ratio. The most obvious criteria are the mean absolute error (MAE) and mean squared error (MSE) [31], [32]. The statistical investigations of 26 different image quality measures [34] using ANOVA analysis [33] have revealed that MAE and MSE remain the best measures for additive noise.

A. GA Optimization of Soft Morphological Filters Using Training Set

Generally, in the case of film restoration, it is not possible to perform a comparison with an ideal image sequence; as such a thing does not exist. After all, if a noncorrupted version of the film exists, why bother trying to restore a corrupted version? One method of addressing this problem is as follows:

In most image sequences, it is generally possible to find areas of the image, which are uncorrupted. Then it is possible to artificially corrupt these ideal image regions with particles of film dirt extracted from other similar, but corrupted, regions of the image sequence. In this way, it will be feasible to produce the necessary training set, which allows the evaluation of a fitness value based on some measure of the MAE and/or MSE. Fig. 2 shows an example of a series of uncorrupted regions extracted from an image sequence and the same sequence after having been artificially corrupted with film dirt.

B. Fitness Function

Having a training set, i.e., an ideal and corrupted version of the same image sequence, enables the fitness value of an individual (i.e. a particular set of filter parameters) to be based on a comparison between the filtered image sequence having been filtered with the filter having the parameters represented by the individual and the ideal image sequence. The fitness of an individual is therefore determined as follows:

Let MAE_{max} be the maximum possible MAE for an image (MAE_{max} would be 255 for 8-bit grayscale images). Let N be the number of images in the training sequence and MAE_i be the MAE for the i^{th} image in the filtered sequence, with respect to the i_{th} image in the ideal sequence. Let fitness_j be the overall fitness of the individual j

$$fit_i = 1 - \left(\frac{mae_i}{MAE_{max}}\right) \tag{8}$$

$$\operatorname{fitness}_{j} = \left(\frac{100}{N}\right) \times \sum_{i=1}^{N} \operatorname{fit}_{i}.$$
(9)

In other words, the "interim" fitness for an image in the sequence is a measure of how it is close to the ideal. The fitness value for an individual is then the average of all these interim fitness values over the whole image sequence, expressed as a percentage. A filter capable of restoring an image sequence perfectly would then have a fitness value of 100.

C. Genetic Operators

Uniform crossover and bit mutation [35], [36] showed promising results when used for the optimization of a soft morphological filter using the GA for the restoration of old film sequences [29].

The actual "genetic algorithm" used in this paper is the Hierarchical GA [12] with the following parameters.



Fig. 2. (a) Six frames of uncorrupted regions extracted from image sequence. (b) The same frames after being corrupted with film dirt.

- Selection: Stochastic universal sampling was used.
- *Crossover:* Uniform crossover was applied with a probability of 0.75.
- *Mutation:* The mutation operator involved randomly choosing one of the possible values of an allele for a particular locus on the chromosome. Mutation was applied with a probability of 0.03.
- Population Size: The population size was set at 30.

Practically, these parameter settings were found to be suitable for the SMF optimization with the given chromosome encoding and structure. They enabled the GA to make good use of the sur-



Fig. 3. Maximum fitness in each generation.

viving chromosomes and a wide exploration of the search space. Also, the best fitness was obtained after a reasonable number of steps. This is shown in Fig. 3. It was found experimentally that there is no need to use different values of these parameters when restoring different film sequences, provided that a sufficiently representative sample of film dirt was included in the original training data. This makes our proposed method simple and applicable to other similar film sequences without any further changes of control parameters.

VI. APPLICATION TO REAL IMAGE SEQUENCES

A GA, as described above, was run using the training set shown in Fig. 2. It was set the task of optimizing a soft morphological filter of a symmetrical structuring function with an overall size set at $7 \times 7 \times 3$ (i.e., spatial dimensions of 7×7 and a temporal dimension of 3). Images extracted from the real noisy sequence are shown in Fig. 4.

LUM [17], [18] is one of the spatio-temporal multistage order statistic filters which showed a good performance in restoring image sequences with the efficient preservation of image features and sequence motion [17]. So, the results of the best obtained SMF were compared to those of the LUM(27,9) applied to the same image sequence. These are shown in Fig. 5. The error images between the ideal and filtered training sequences using the best obtained SMF and LUM(27,9) are shown in Fig. 6.

Fig. 3 shows the maximum fitness at each generation during the GA's run. The maximum obtained fitness after 500 generations was 99.52 while the fitness value for the LUM(27,9) was 98.56. The best soft morphological filter found is shown in Fig. 7. This filter was then applied to the entire image sequence. The results of applying the optimized SMF to a real noisy image sequence are shown in Fig. 8.

Also, the proposed method was compared to the so-called spatio-temporal local filtering approach. This method depends on the detection of the noise using the ROD detector [19] then filtering the sequence with the ML3Dex filter [20]. It filters the detected noisy pixels and leaves the remaining image pixels untouched. To be able to compare the proposed method with the spatio-temporal local filtering approach, the optimized filter was applied to the image sequence after noise detection such that,



Fig. 4. Images extracted from the real noisy sequence.



Fig. 5. Images extracted from the real noisy sequence after filtering with the LUM(27,9) filter.

the noisy pixels were filtered using the optimized SMF with the optimum rank, and the remaining image pixels were filtered with the same filter but with a rank equal to the boundary cardinality. The fitness value of the ML3Dex filter with noise detection was found to be 99.54. The optimized SMF with noise



Fig. 6. (a) Error images between the clean sequence and the filtered sequence with the SMF. (b) Error images between the clean sequence and the filtered sequence with the LUM(27,9) (these images have been negated such that the darker pixels indicate the errors).

detection showed a high fitness value of 99.88. The results of applying the ML3Dex filter and the optimized SMF, after noise detection, to a real image sequence are shown in Figs. 9 and 10, respectively.

VII. DISCUSSION

It can be seen that the best SMF found has some characteristics expected of a suitable filter. For instance, the hard center has a support of one pixel, which lies at the origin of the structuring 2 6

4

2

6

4

4 6

413

Soft Boundary

						the second second
0	*	*	6	*	*	0
*	3	6	4	6	3	*
*	*	*	2	*	*	*
5	6	4	4	4	6	5
*	*	*	2	*	*	*
*	3	6	4	6	3	*
0	*	*	6	*	*	0
6	6	6	6	6	6	6
*	4	4	6	4	4	*
2	*	4	*	4	*	2
			· · · · ·			1

2 6

*

4 4

6

4

6 6 6 6

0	*	*	6	*	*	0
*	3	6	4	6	3	*
*	*	*	2	*	*	*
5	6	4	4	4	6	5
*	*	*	2	*	*	*
*	3	6	4	6	3	*
0	*	*	6	*	*	0

Repetition Parameter = 71

Filter Sequence: Soft Dilate Soft Erode

function (i.e., the pixel under consideration). So, the output of the filter is weighted toward the input pixel value. Also, the filter sequence found is soft-dilation soft-erosion. This might be expected for the removal of dark artifacts within the image. However, due to the nature of soft morphological filters, the relationship between filter parameters and their effects are not quite as intuitive as for standard morphological filters.

As illustrated in the Introduction, impulsive distortions damaging old films are mainly caused by film dirt. This film dirt manifests as dark and bright patches of different shape and size. Individual pixels in a blotch are a kind of impulsive noise distortion. The initial soft morphological filter used was of spatial dimension 7×7 , which means that dirt of dimension less than 7×7 will be filtered out. So, the maximum cardinality of C, [C], will be 49. Also, the filter found has boundary cardinality $|\mathbf{b}| = 206$, center cardinality $|\mathbf{a}| = 1$, and rank $\mathbf{r} = 71$. Substituting these values in (9) was shown to satisfy the inequality. Hence, the filter found could filter out the dark as well as the bright blotches. This is clear in Fig. 8.

In general, the results depicted in Fig. 8 show that the filter found has excellent performance in attenuating/removing film dirt from image sequences and has little, if any, effect on the



Fig. 8. Images extracted from the real noisy sequence after filtering with the optimized SMF.



Fig. 9. Images extracted from the real noisy sequence after filtering with the ML3Dex filter with noise detection.

image detail. Also, the fast-moving objects were accurately restored even though no motion compensation was applied.

Fig. 10. Images extracted from the real noisy sequence after filtering with the optimized SMF with noise detection.



Fig. 11. Histogram of the error images between the clean and the filtered sequence using the best obtained SMF averaged over the training sequence.



Fig. 12. Histogram of the error images between the clean and the filtered sequence using the LUM(27,9) averaged over the training sequence.

Figs. 11 and 12 show the histograms, averaged over the training sequence, of the error images between the clean and the filtered sequences using the best obtained SMF and LUM (27,9), respectively. It is clear that LUM filter results in more



Fig. 13. Three consecutive frames extracted from the real noisy sequence: (a) the real noisy frames, (b) the result of LUM(27,9) filtering; (c) the result of ML3Dex filtering with noise detection; and (d) the result of optimized SMF filtering.

errors than the best obtained SMF. The results depicted in Fig. 5 show good removal of the noise but the LUM filter was not capable of restoring the fast-moving objects in the image sequence. This is clear in Fig. 13.

Compared to ML3Dex with noise detection, SMF with noise detection showed no difference in the subjective quality of the restored images. Also, it could perfectly restore all fast-moving objects while the ML3Dex failed to do this. A challenging sequence is shown in Fig. 13. In addition to their rotational motion, which is very difficult for any motion-estimation technique to compensate for, the propellers appear in one frame but are not present in either the preceding or the succeeding frame. In this case, no known motion-estimation technique can estimate this type of motion as it exceeds the Nyquist sampling limit set by the frame rate. An obvious advantage of the SMF with noise detection is its robustness to false noise detection, such that false noise pixels are filtered by the SMF with the optimum rank.

In spite of the SMF being optimized for a small, artificially created training set, the filter still performs well when applied to the entire image sequence.¹ The automatic restoration of film sequences using the proposed method possessed the following advantages: no user determined parameters, good noise removal with minimum distortion of the image objects, and perfect restoration of all fast-moving objects without motion compensation.

VIII. CONCLUSIONS

In this paper, a technique is developed for the optimization of multidimensional grayscale soft morphological filters using the GA. The method optimizes filters with respect to a criterion based on mean absolute error. This criterion necessitates the creation of an artificial training set. However, it has been shown that this is not an overly burdensome task. The filter is extended to the spatio-temporal domain to make use of the temporal characteristics of the video sequence and coded such that the GA is free to search for the optimum filter among the purely spatial, purely temporal and spatio-temporal filters. The optimized SMF showed excellent performance in attenuating/removing film dirt from image sequences and has little, if any, effect on the image detail. Although the proposed optimization method does not contain motion compensation, which adds more complexity to the algorithm, the fast-moving objects were restored perfectly. The proposed method is compared to two other methods for film restoration. In the first method, a so-called global filtering approach, a LUM filter was used. The second method is dependent on the detection of the noise pixels and then applying the ML3Dex filter to only the detected noisy pixels leaving the other pixels untouched. The results obtained by applying the optimized SMF to a real image sequence, showed improved performance compared to the LUM filter for the removal of the film dirt and outperformed the LUM filter in restoring the fast-moving objects in the image sequence. To be able to compare the proposed method with the ML3Dex filter with noise detection, the SMF was applied to the image sequence after noise detection as explained in Section VI. While SMF with noise detection showed no difference in the visual quality when compared to ML3Dex with noise detection, it showed better performance in restoring the fast-moving objects, which the ML3Dex filter failed to restore.

Because of the advantages of the proposed method, demonstrated in Section VII, and the achieved perceptual quality of the restored film sequence, the proposed method proved to be a simple, fast, and cheap approach for the automatic restoration of old film archives.

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REFERENCES

- M. Chong, S. Kalra, D. Krishnan, and A. Laud, "Computerized motion picture restoration system," in *Proc. BroadcastAsia98*, 1998, pp. 153–159.
- [2] L. Rosenthaler, A. Wittmann, A. Giinzl, and R. Gschwind, "Restoration of old movie films by digital image processing," in *Proc. IMAGE'COM* 96, Bordeaux, France, May 1996, pp. 1–6.
- [3] A. Kokaram, R. Morris, W. Fitzgerld, and P. Rayner, "Detection of missing data in image sequences," *IEEE Trans. Image Processing*, vol. 4, pp. 1496–1508, Nov. 1995.
- [4] J. Gallagher and G. Wise, "A theoretical analysis of the properties of median filters," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-29, pp. 1136–1141, Dec. 1981.
- [5] H. Senel, R. Peters, and B. Dawant, "Topological median filters," *IEEE Trans. Image Processing*, vol. 11, pp. 89–104, Feb. 2002.
- [6] A. Nieminen, P. Heinonen, and Y. Neuvo, "A new class of detail-preserving filters for image processing," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. PAMI-9, pp. 74–90, Jan. 1987.
- [7] G. Arce and E. Malaret, "Motion preserving ranked-order filters for image sequence," in *Proc. IEEE Int. Symp. Circuits and Systems*, vol. 2, New York, May 1989, pp. 983–986.
- [8] B. Alp, P. Haavisto, T. Jarske, K. Oistamo, and Y. Neuvo, "Median-based algorithms for image sequence processing," in *Proc. SPIE Int. Society Optical Engineering*, vol. 1360, 1990, pp. 122–134.
- [9] A. Kokaram and S. Godsill, "A system for reconstruction of missing data in image sequences using sampled 3D AR models and MRF motion priors," in *Proc. Eur. Conf. Computer Vision ECCV'96*, vol. 2, 1996, pp. 613–624.
- [10] —, "MCMC for joint noise reduction and missing data treatment in degraded video," *IEEE Trans. Signal Processing*, vol. 50, pp. 189–205, Feb. 2002.

¹In order to give the reader a better impression of the restoration including motion, the full set of the clean and noisy training sequences, as well as the noisy and filtered real sequences, is available at: [Online] http://www.spd.eee.strath.ac.uk/~mahmoud/film_restoration.html

- [11] K Tang, K. Man, S. Kwong, and Q. He, "Genetic algorithms and their applications," *IEEE Signal Processing Mag.*, vol. 13, pp. 22–37, Nov. 1996.
- [12] K. Man, K. Tang, and S. Kwong, *Genetic Algorithms: Concepts and Design*. New York: Springer, 1999.
- [13] R. Davies and T. Clarke, "Parallel implementation of a genetic algorithm," *Control Eng. Practice*, vol. 3, no. 1, pp. 11–19, Jan. 1995.
- [14] W. Rivera, "Scalable parallel genetic algorithms," Artific. Intell. Rev., vol. 16, no. 2, pp. 153–168, Oct. 2001.
- [15] G. Sena, D. Megharbi, and G. Isern, "Implementation of a parallel genetic algorithm on a cluster of workstations: travelling salesman problem, a case study," *Future Gener. Comput. Syst.*, vol. 17, no. 4, pp. 477–488, Jan. 2001.
- [16] K. Ji, K. Tae, D. Sung, and L. Chong, "Development of FPGA based adaptive image enhancement filter system using genetic algorithms," in *Proc. 2002 Congress Evolutionary Computation*, vol. 2. Piscataway, NJ, USA, 2002, pp. 1480–1485.
- [17] G. Arce, "Multistage order statistic filters for image sequence processing," *IEEE Trans. Signal Processing*, vol. 39, pp. 1146–1163, May 1991.
- [18] R. Hardie and C. Boncelet, "LUM filters: a class of rank-order-based filters for smoothing and sharpening," *IEEE Trans. Signal Processing*, vol. 41, pp. 1061–1076, Mar. 1993.
- [19] M. Nadenau and S. Mitra, "Blotch and scratch detection in image sequences based on rank ordered differences," in *Proc. 5th Int. Workshop* on *Time Varying Image Processing and Moving Object Recognition*, Sept. 1996, pp. 27–35.
- [20] A. Kokaram, *Motion Picture Restoration*. Berlin, Germany: Springer, 1998.
- [21] C. Pu and F. Shih, "Soft mathematical morphology: binary and greyscale," in Proc. Int. Workshop on Mathematical Morphology and its Applications to Signal Processing, Barcelona, Spain, May 1993, pp. 28–33.
- [22] P. Kuosmanen, P. Koivisto, H. Huttunen, and J. Astola, "Shape preservation criteria and optimal soft morphological filtering," J. Mathemat. Imaging and Vis., vol. 5, no. 4, pp. 319–335, Dec. 1995.
- [23] L. Koskinen, J. Astola, and Y. Neuvo, "Soft morphological filters," in Proc. SPIE Int. Society for Optical Engineering, vol. 1568, July 1991, pp. 262–270.
- [24] C. Pei, L. Lai, and F. Shih, "Recursive order-statistic soft morphological filters," *Proc. IEE Vision Image and Signal Processing*, vol. 145, no. 5, pp. 333–342, Oct. 1998.
- [25] P. Kuosmanen and J. Astola, "Soft morphological filtering," J. Mathemat. Imaging and Vis., vol. 5, no. 3, pp. 231–262, Sept. 1995.
- [26] H. Huutunen, P. Kuosmanen, L. Koskinen, and J. Astola, "Optimization of soft morphological filters by genetic algorithms," in *Proc. Image Algebra and Morphological Image Processing V*, San Diego, CA, July 1994.
- [27] P. Kuosmanen, P. Koivisto, H. Huutunen, and J. Astola, "Optimization of soft morphological filters under shape preservation criteria," in *Proc. Image Algebra and Morphological Image Processing V*, San Diego, CA, July 1994.
- [28] R. Srinivasan, "Image restoration by spatial filter design," in *Proc. SPIE* Int. Society for Optical Engineering, vol. 707, 1986, pp. 193–197.
- [29] N. Harvey and S. Marshall, "Film restoration using soft morphological filters," in *Proc. 6th Int. Conf. mage Processing and its Applications* (*IPIA'97*), Dublin, Ireland, July 1997, pp. 279–282.
- [30] J. Holland, Adaptation in Natural and Artificial Systems. Cambridge, MA: MIT Press, 1992.
- [31] K. Topfer and R. Jacobson, "The relationship between objective and subjective image quality criteria," J. Information Recording Material, vol. 21, pp. 5–27, 1993.
- [32] R. Jacobson, "An evaluation of image quality metrics," J. Photog. Sci., vol. 43, pp. 7–16, 1995.
- [33] A. Rencher, *Methods of Multivariate Analysis*. New York: Wiley, 1995.
- [34] I. Avcibas, B. Sankur, and K. Sayood, "Statistical evaluation of image quality measures," *J. Electron. Imaging*, vol. 11, no. 2, pp. 206–223, Apr. 2002.

- [35] G. Syswerda, "Uniform crossover in genetic algorithms," in Proc. 3rd Int. Conf. Genetic Algorithms, June 1989, pp. 2–9.
- [36] J. Page, R. Poli, and W. Langdon, "Smooth uniform crossover with smooth point mutation in genetic programming: a preliminary study," in *Proc. Genetic Programming, 2nd European Workshop EuroGP'99.* Berlin, Germany: Springer-Verlag, 1998, pp. 39–48.



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