COMBINING THE HEURISTIC AND SPECTRAL DOMAINS IN SEMI-AUTOMATED SEGMENT GENERATION

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ABSTRACT:

The generation of thematically accurate image segments or delineating land-cover elements is a common objective and challenge in Geographic Object Based Image Analysis (GEOBIA). A core notion to the applicability of segmentation algorithms for partitioning these land-cover elements is that said elements typically have some spectral or other homogeneity criteria that allow successful segmentation, to varying degrees. One approach that addresses this challenge models the parameterised segmentation process as a search problem. The search method is provided with a reference of optimal desired output. This idea is extended in this work by suggesting the encoding of spectral space transformations as additional variables to such a search problem. The automatic exploration and transformation of the spectral domain can allow for a closer correlation between thematic and spectral similarity of the land-cover elements of interest, thus aiding the segmentation process. Two simple spectral transformation methods functioning in conjunction with two scale-space constraint image segmentation algorithms are presented to illustrate this concept. A statistically significant improvement in segmentation results can be obtained consistently in acceptable time with this approach with off-the-shelf meta-heuristics for our test areas. It is also shown with the algorithms used in this study that the segmentation algorithm parameters (heuristic domain) are dependent on the spectral transformation parameters (spectral domain) to achieve optimal results. This necessitates simultaneous optimisation of these two domains.

1. INTRODUCTION

Image segmentation is a ubiquitous paradigm in scientific disciplines that are concerned with information extraction from imagery. In the discipline of remote sensing, thematically accurate segments, or geographic objects, are typically the desired end result of a segmentation process. The semi-automation of generating these geographic-objects (single or multi-scale) holds value in domains concerned with monitoring or emergency response mapping, where user interaction is required to be non-exhaustive and turnover times short. In such a context the emphasis falls on user assisted information extraction rather than full autonomy of the information extraction process or using extensive pre-developed solutions.

One school of thought moderates the process of semi-automated object or geographic-object generation to an optimisation problem (Bhanu et al., 1995; Pignalberi et al., 2003; Feitosa et al., 2006; Fredrich & Feitosa, 2008; Derivaux et al., 2010). The search space of all possible results, or segment sets, is traversed to find a solution that most closely matches a small reference set provided by a user. Empirical discrepancy metrics (Zhang, 1996), especially area based accuracy metrics (Pignalberi et al. 2003; Fredrich & Feitosa, 2008; Feitosa et al., 2010), are commonly employed to judge the resemblance of any segment set and the reference set. It is assumed that if the given segmentation algorithm and parameter(s) are adequate for segmenting the reference; it will be adequate for previously unseen examples.

The search space of such an approach usually consists of the real or discrete valued parameters of the segmentation algorithm employed. Due to the potentially complex and large search spaces, coupled with the computationally expensive nature of image segmentation, stochastic population based search methods are preferred. No guarantees can be made that the optimal solution can be found or if a quality solution even exists for the given scenario. Results remain dependent on the inherent suitability of the segmentation algorithm to the problem. To our knowledge, thus far only the segmentation algorithm parameters, or the Heuristic Domain (HD), are considered variables to such a method.

Another line of research considers the effects different colour or spectral space representations of the input data have on the performances of image processing tasks. Examples include measuring the effects different colour space representations have on image segmentation (Busin, Vandenbroucke & Macaire, 2008; Kwok, Ha & Fang, 2009), automatic iterative colour space selection for a given segmentation problem (Busin et al., 2004) and the application and derivation of illumination invariant colour spaces (Chong, Gortler & Zickler, 2008; Shan, Yan & Wang, 2007).

The concept of modelling example driven segmentation as a search problem is extended by suggesting the addition of simple measures of Spectral Domain (SD) transformation within the search function. Inspired by the abovementioned work on colour space transformations and concepts of low-mid-high level image processing cue integration (Kumar, Torr & Zisserman, 2010), it is suggested that low-level (image transformation) and mid-level (image segmentation) image processing steps are combined and optimised simultaneously. Typically, any analysis, refinement or classification will be done on original untransformed spectral data, although bounded by segment borders derived with the help of additional image processing steps.

Closer correlations between spectral and thematic similarity can be found if the data is allowed to be transformed, assisting the

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segmentation algorithm on the user defined problem. It is also briefly shown here that these two domains are interdependent and needs to be optimised simultaneously in our experiments.

It is not uncommon for users to use expert knowledge of the problem at hand in defining optimal input to a segmentation problem, for example segmenting with a vegetation index band (EVI, NDVI) if concerned with a vegetation application. It is suggested that the user can be unburdened with this task if examples of desired output are available.

In section 2 of this paper the method for simultaneously optimising the spectral and heuristic domains is presented, along with some details on the search algorithms, segmentation algorithms, fitness functions and spectral transformation functions implemented. Section 3 describes the study area and test data used. Quantitative comparisons of the proposed extension to the original method are presented in Section 4. Conclusions on the characteristics of the method and suggestions for future work are presented in Section 5.

2. OPTIMISING ALGORITHM AND SPECTRAL TRANSFORMATION PARAMETERS

2.1 Combined heuristic and spectral domain search

The proposed method to simultaneously optimise the heuristic domain (segmentation algorithm parameters) and the spectral domain (transformed image input used in segmentation) is illustrated in Figure 1 (hereafter called HD + SD search). HD + SD search consists of a core optimisation layer giving and receiving input from a fitness score generation layer, which in turn receives input from a simple image input layer.

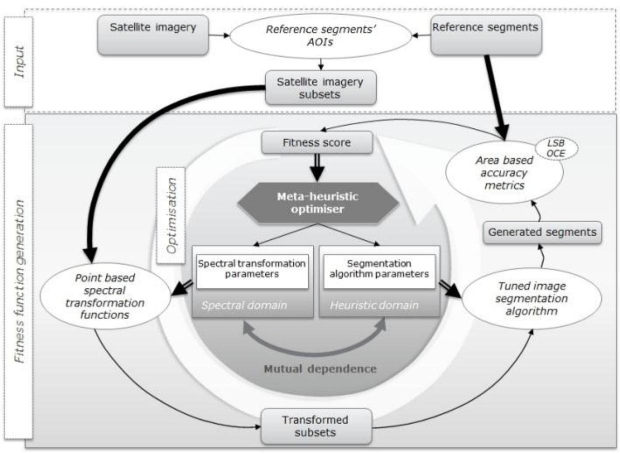

Figure 1. Method for simultaneously optimising the spectral and heuristic domains in semi-supervised segment generation (SD + HD search).

As input, the method accepts a multi-band image and a Boolean raster of the same dimensions, delineating reference segments of desired outputs. Small subsets of the satellite image, centred on the coordinates (areas of interest) of the user defined reference segments, are extracted and used for all subsequent processing. Subsetting saves computing time by avoiding repeated segmentation of unnecessary areas.

The core of the method consists of an iterative optimisation/search algorithm taking as input a single value, called the fitness score. Optimisers employed are presented in section 2.2. As output the optimisation algorithm produces multidimensional real and/or discrete valued sets depicting spectral transformation parameters (SD) and segmentation algorithm parameters (HD). The dimensionality of the overall problem depends on the used segmentation algorithm and spectral transformation method.

During iterations of the optimisation algorithm the fitness score generation layer is invoked and provided with SD and HD parameter sets provided by the optimisation layer. The SD parameters are used as input to a transformation function that changes the spectral space representation of the imagery subsets, resulting in new transformed subsets. Two simple transformation functions are employed and described in section 2.3. These transformed subsets are used as input to a segmentation algorithm tuned with the HD parameters provided by the optimisation layer. Two segmentation algorithms are tested with this approach and are described in section 2.4. The resulting generated segments are evaluated against the reference segments (taken from the input layer) with the aid of area based empirical discrepancy metrics (described in section 2.5.), producing the fitness score. Subsequently the fitness score is returned to the optimisation layer, invoking a new iteration of the optimisation algorithm.

The SD + HD method terminates after a certain number of iterations of the search algorithm have been performed. The output of the SD + HD search is an interdependent spectral transformation parameter set and segmentation algorithm parameter set that was found most suited to the problem (as judged by the fitness function).

2.2 Optimisers

Two common stochastic population based meta-heuristic optimisers were implemented and tested in this study, namely the Differential Evolution (DE) (Storn & Prince, 1995) algorithm and the Particle Swarm Optimisation (PSO) (Kennedy & Eberhart, 1995) algorithm. Multi-objective meta-optimisation (Pederson & Chipperfield, 2009) was performed on both algorithms to tune their controlling parameters. Figure 2 illustrates typical fitness curves observed with these two algorithms for our example problems. For all our experiments it was found that between 600 and 1000 iterations were sufficient to achieve near optimal solution fitness. The DE strategy provided slightly better final fitness scores compared to a standard PSO strategy and was subsequently used for all further experimentation.

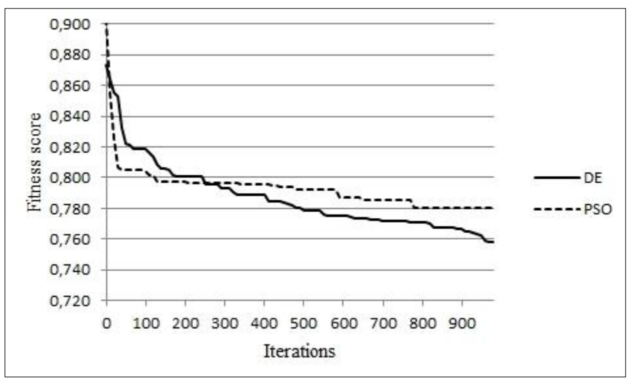

Figure 2. A typical example of fitness traces generated with the meta-optimised DE and PSO algorithms on HD + SD search problems.

2.3 Spectral transformation functions

Two transformation methods are implemented, namely a transformation matrix and a simple histogram modification function. All used images have three spectral bands. The transformation matrix converts the original three band spectral space $(b1, b2, b3)$ to a new space $(n1, n2, n3)$ with the following equation:

$$\begin{bmatrix} n1 \\ n2 \\ n3 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \times \begin{bmatrix} b1 \\ b2 \\ b3 \end{bmatrix} \quad (1)$$

Where variables a through i define the transformation matrix and have numerical bounds of [-0.2, 1] in our tests.

The histogram modification function, called spectral split, consists of four variables. Three variables define positions (*p1*, *p2*, *p3*) within the histograms of the three separate bands (range of [0, 255]), while the fourth (*h*) defines the magnitude with which pixels around these points in the histogram are modified. If a pixel *value* in band *x* satisfies any of the following two conditional statements it is changed accordingly:

If $value_x < p_x$ and $value_x > p_x - h$ then $value_x = value_x - (h - p_x - value_x)$.
If $value_x > p_x$ and $value_x < p_x + h$ then $value_x = value_x + (h - value_x - p_x)$.

These two point based image transformation functions only modify spectral values based on their own values and either some variables (in the case of spectral split) or variables and spectral values of other bands (in the case of the transformation matrix). Using spectral split adds an additional four variables to the optimisation problem, while using the transformation matrix adds an additional nine.

2.4 Segmentation algorithms

The HD + SD search method is tested with two segmentation algorithms, namely the Simple Linear Iterative Clustering (SLIC) (Radhakrishna et al., 2010) algorithm and a region merging segmentation algorithm variant, called Multiresolution Segmentation (MS) (Baatz & Schäpe, 2000). As the name suggests SLIC is an iterative clustering segmentation algorithm (K-means) combining the spectral and spatial properties/dimensions of an image into a single Euclidian space. Regions or segments are clustered in an unsupervised manner in this combined spectral/spatial space. The SLIC algorithm holds two parameters, one called "Scale" controlling relative segment size and "M"; controlling segment compactness. SLIC was developed for generating superpixels to be used in a parts-based information extraction paradigm. It is used with some liberty here in a thematic segmentation context due to algorithm elegancy/simplicity and speed efficiency.

The MS region merging algorithm has three main parameters entitled „Scale", „Colour" and „Compactness". Additional parameters control the contributions (weights) that the different image input bands have in influencing segment merging. Interestingly, this simple form of band weighting constitutes a low-level image processing or modification task; encoded within the actual segmentation algorithm. For simplicity bands are not weighted in this work.

Concerns could be raised regarding the practical feasibility (computing time) of modelling semi-supervised segmentation as a search problem. It can be noted that in our experiments with the SD + HD search method using SLIC as the segmentation algorithm the search process typically finished after 1-2 minutes while the MS algorithm took 4-5 minutes (standard desktop computer with no algorithm multithreading or code optimisations, using very high resolution (VHR) imagery and numerous reference segments).

2.5 Empirical discrepancy metrics

Two area-based empirical discrepancy metrics are implemented and tested with the HD + SD search method, namely the Larger Segments Booster (LSB) (Fredrich & Feitosa, 2008) and a modified version of the Object-level Consistency Error (OCE) (Polak et al., 2009). Both these metrics can compensate for over- and under-segmentation. Both use measures of false positives and false negatives to quantify the percentage of overlap; however they strongly differ in their implementations of handling over-segmentation.

The LSB metric compensates for over-segmentation by counting the number of pixels intersecting the reference segment and using this value as a penalisation factor. The OCE metric handles false positives and false negatives per individual segment that has some overlap with the reference segment. With OCE, over-segmentation is penalised via the summation of individual segment overlap results; weighted by the percentage cover of said overlap with the reference segment (see Polak et al., 2009 for a full formulation). Both metrics have a numerical range of [0, 1] with a value of 1 indicating no match and a value of 0 indicating a perfect match with the reference segments.

3. TEST AREA AND DATA

The viability and characteristics of the proposed method is demonstrated via the task of identifying habitable structures in Internally Displaced Persons (IDP) camps in East Africa. Relief agencies need accurate estimations of the number and sizes of habitable structures in these camps to model population size. GeoEye-1 and QuickBird imagery subsets (5 ha – 50 ha) of three IDP camps, in Kenya, Somalia and Ethiopia were selected, for simplicity referred to by their hosting countries.* Land-cover mapping and structure counting of these settlements are routinely performed to provide relief agencies with updated maps and information.

The three sites display different structure characteristics (see Figure 3). The Ethiopia site mainly consists of easily identifiable white tents or huts draped with white tent nylon. The land-cover elements of interest thus display strong within element spectral homogeneity and are also relatively homogeneous in the scale-space. One could practically use a single-scale segmentation approach for this site. The other two sites (Kenya and Somalia) display different structural and spectral characteristics and variation in structure size, constituting a more difficult problem. In practise a multi-class and multi-scale approach would be suggested for these sites. To demonstrate the SD + HD search method, it is attempted to segment all structures using a single segmentation layer and thematic class. For each site between ten and twenty reference structures were digitised, to be used as reference segments input.

* EO data provided by the ESA managed GSC-DA, funded under ESA – EC Agreement on the Implementation of the Space Component of Global Monitoring for Environment and Security (GMES).

4. RESULTS AND DISCUSSION

4.1 Heuristic domain search versus combined heuristic and spectral domain search

The HD + SD search method is quantitatively compared with the variant of semi-supervised segmentation not performing any spectral space transformations. For each test site (Ethiopia, Kenya and Somalia) the search methodology is tested by performing no spectral space transformations, using spectral split and the transformation matrix; on both segmentation algorithms implemented. Experiments for each problem scenario were repeated for 25 runs to obtain a measure of the standard deviation of the results. Table 1 lists the mean metric fitness scores and standard deviations obtained using the OCE metric, while Table 2 lists the same using the LSB metric.

OCE		No transformation	Spectral split	Transformation matrix
Ethiopia	SLIC	0,47 ±0,00	0,44 ±0,02	0,37 ±0,01
	MS	0,35 ±0,01	0,32 ±0,02	**0,28 ±0,03**
Kenya	SLIC	0,80 ±0,00	0,78 ±0,01	0,71 ±0,02
	MS	0,77 ±0,01	0,75 ±0,01	**0,69 ±0,02**
Somalia	SLIC	0,80 ±0,01	0,78 ±0,01	0,73 ±0,02
	MS	0,76 ±0,00	0,76 ±0,01	**0,67 ±0,02**

Table 1. OCE metric scores comparison of the HD + SD search approach versus a HD only approach.

LSB		No transformation	Spectral split	Transformation matrix
Ethiopia	SLIC	0,48 ±0,00	0,47 ±0,01	0,45 ±0,01
	MS	0,44 ±0,01	0,41 ±0,01	**0,41 ±0,02**
Kenya	SLIC	0,83 ±0,00	0,79 ±0,01	**0,68 ±0,02**
	MS	0,79 ±0,01	0,77 ±0,02	0,68 ±0,02
Somalia	SLIC	0,91 ±0,00	0,87 ±0,01	0,76 ±0,02
	MS	0,84 ±0,02	0,82 ±0,02	**0,70 ±0,01**

Table 2. LSB metric scores comparison of the HD + SD search approach versus a HD only approach.

Tables 1 and 2 illustrate marked improvement in average metric scores when employing spectral domain transformation functions within the search method. In all examples the simple transformation matrix approach produced the best results. In our experiments using a meta-optimised DE search algorithm very small standard deviations in obtained results are observed; potentially an indication that optimal results for these scenarios are reached, bearing in mind segmentation algorithm and spectral transformation function capabilities. Such a methodology can also be used to compare different segmentation algorithms for a given application and in selecting a proper spectral transformation function.

The distributions of the HD versus HD + SD search results are all statistically significant with a 1% confidence interval (student's t-test). The results achieved with the best combination of segmentation algorithms and spectral transformation functions are typed in bold.

Figure 3 shows the best performing segmentations achieved (small subsets) using SLIC for all three sites using the HD only search strategy (3(a), 3(d), 3(g)) compared with that of a HD + SD search using spectral split (3(b), 3(e), 3(h)) and a transformation matrix (3(c), 3(f), 3(i)).

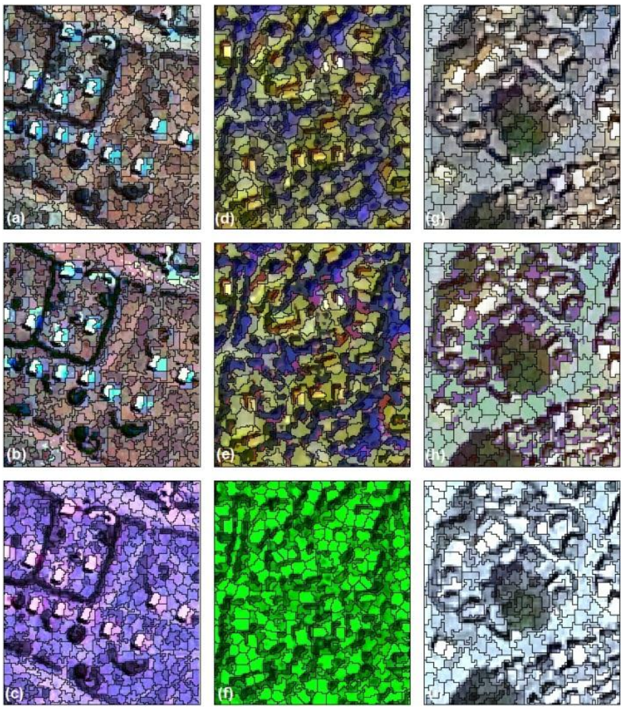

Figure 3. Best performing segmentation results for the Ethiopia (a-c), Kenya (d-f) and Somalia (g-i) test sites.

4.2 A luminance-chrominance space as base input

The above experiment is repeated by using a luminance-chrominance colour space as the basic input to the HD and HD + SD search methods. One dimension of the CIELAB luminance-chrominance colour space (L) used here defines brightness while the other two dimensions (A and B) define the colour components. Using the CIELAB colour space as base representation is compared with the original red, green and blue (RGB) colour space to illustrate the potential of using more elaborately transformed colour spaces; although selected in a non-automated manner in this example. Table 3 lists the results for the Kenya test site using the OCE metric as fitness function.

Kenya		No transformation	Spectral split	Transformation matrix
SLIC	RGB	0,80 ±0,00	0,78 ±0,01	0,71 ±0,02
	CIELAB	0,77 ±0,00	0,76 ±0,01	**0,68 ±0,02**
MS	RGB	0,77 ±0,01	0,75 ±0,01	0,69 ±0,02
	CIELAB	0,74 ±0,01	0,71 ±0,01	**0,62 ±0,03**

Table 3. OCE metric scores comparing RGB and CLIELAB colour spaces as base input to the HD and HD + SD search methods.

For this specific problem the use of a luminance-chrominance colour space improved the results, irrespective of the spectral transformation method used. A substantial improvement in results is observed comparing the use of the original RGB colour space (No transformation) with the CIELAB space using the spectral transformation matrix.

4.3 Comparison of heuristic domain parameter values using different spectral domain transformation techniques

The dependence of the HD parameters on the used SD method and parameters is illustrated in Tables 4 and 5. Table 4 lists the average parameter values of the SLIC algorithm obtained (best results) for the three test sites while Table 5 lists the same for the MS algorithm.

SLIC		No transformation	Spectral split	Transformation matrix
Ethiopia	Scale	6,00 ±0,00	6,24 ±0,59	5,96 ±0,20
	M	33,40 ±0,75	31,04 ±9,24	28,20 ±6,75
Kenya	Scale	7,16 ±0,54	7,48 ±1,55	7,40 ±2,10
	M	32,64 ±5,47	29,12 ±7,36	33,92 ±5,15
Somalia	Scale	5,00 ±0,00	5,48 ±0,75	5,64 ±0,48
	M	31,76 ±6,84	29,60 ±7,87	28,96 ±7,30

Table 4. Average SLIC parameters obtained using the HD and HD + SD search methods.

MS		No transformation	Spectral split	Transformation matrix
Ethiopia	Scale	12,88 ±0,52	16,68 ±7,49	8,52 ±4,30
	Colour	0,10 ±0,00	0,27 ±0,28	0,32 ±0,31
	Compactness	0,97 ±0,07	0,75 ±0,29	0,71 ±0,25
Kenya	Scale	14,72 ±2,20	11,68 ±2,62	7,32 ±1,64
	Colour	0,11 ±0,01	0,11 ±0,01	0,15 ±0,11
	Compactness	0,77 ±0,10	0,83 ±0,19	0,72 ±0,22
Somalia	Scale	8,48 ±0,70	9,28 ±1,64	6,04 ±1,71
	Colour	0,10 ±0,01	0,11 ±0,02	0,19 ±0,17
	Compactness	0,90 ±0,06	0,88 ±0,13	0,84 ±0,17

Table 5. Average MS parameters obtained using the HD and HD + SD search methods.

The standard deviation of the Scale parameter of the SLIC algorithm (Table 4) is low with a slight difference in mean values when comparing different SD transformation techniques. In contrast, the M parameter displayed large deviation in optimal results, suggesting the Scale parameter to be of greater importance to the problem. Figure 4 illustrates this notion by plotting fitness results obtained by segmenting a test area with all combinations of Scale and M parameters (no SD transformations).

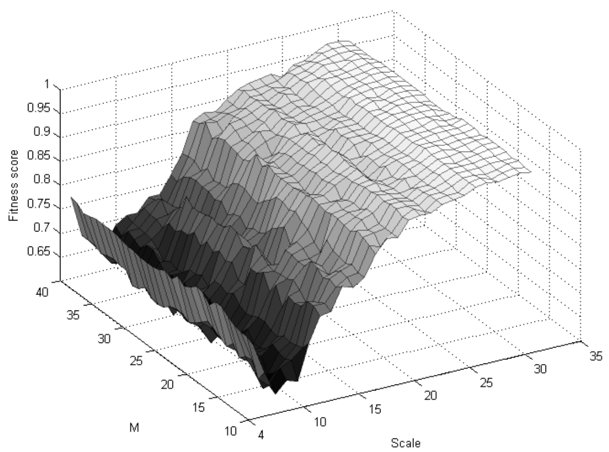

Figure 4. Fitness plot of the SLIC parameters for an arbitrary problem.

In contrast to the SLIC algorithm parameters, the MS parameters showed marked differences (Table 5) in optimal HD parameters obtained using different SD transformation techniques, suggesting stronger parameter interdependence for this algorithm. These results illustrate the influence of the SD parameters on the optimal HD parameters. The amount of influence that the SD parameters have on optimal HD parameters depends on the nature of the segmentation algorithm under consideration.

5. CONCLUSION

In this study a general methodology that combines the search for effective spectral transformation function parameters and segmentation algorithm parameters in a single search problem was presented and tested. The method was compared with a simpler variant where no input data modification is performed, and was shown to improve results measured via area based empirical discrepancy metrics. It should be noted that the capabilities and performances of the employed meta-heuristics, segmentation algorithms, spectral transformation methods and fitness functions should be carefully considered in such an approach. Specific algorithms might perform poorly on certain problems.

Investigating this methodology with segmentation algorithms less constraint in the scale space is called for. Encoding more complex spectral transformation techniques, briefly demonstrated in section 4.2 by using a static luminance-chrominance colour space as base input, might prove useful. Transformation functions that modify spectral values based on neighbourhood properties, or so called neighbourhood operators, could also potentially aid in generating better segments. Efficiency in generalizability of such an approach will constitute future research, specifically investigating the performances of candidate low-level transformation techniques on commonly used segmentation algorithms and mapping problems.

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