論文の内容の要旨

Automatic Image Noise Type Determination Based on Directional Edge Information
(方向性エッジ情報を用いた画像ノイズの自動分類)

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Abstract

The majority of noise-filtering algorithms available in the literature assume that the nature of the noise and its statistical parameters are known a priori. Whereas in most practical applications, we have no accurate information on the type of noise present in an image. This pre-processing phase, prior to noise filtering, the present work positions itself. The output of this system can then be used to influence or tweak any subsequent noise filtering. Automatic Noise Type Determination essentially means, research into methodologies that automatically analyze an image and then determines what is the type of the most predominant video noise in that image and returns an output such as an 'A, B or C' type of answer. In addition, an estimate of the intensity of the strongest noise is also suggested. Then, armed with this information, the most appropriate noise filter can then be applied to the image to clean it in the best way possible. What's more, using the estimated intensity the noise filter can be adjusted depending on how strongly the image is corrupted. One of the major concerns when identifying the type of noise dominant in an image is that some types of noise are content-dependant, and some are content-independent. In other words, the data of the image itself can in some cases influence the intensity of the noise. The easiest way to imagine this is to compare additive noise with multiplicative noise. In the case of additive noise, the resulting corrupted pixel is simply distorted by an offset,

however in the case of multiplicative noise as the pixel's value approaches zero, the same noise signal will have less effect on that pixel whereas as the pixel's value increases towards 255, the same noise signal multiplied by 255 will be greatly increased. Therefore, with these difficulties in mind, a modular strategy was developed using several specialized "expert systems" designed to analyze an image and look for certain features and determine the intensity of one specific noise type and can also provide a certainty factor. So that once the complete system is assembled, a "best guess" with an estimate at the noise level present in the image is produced. The architecture is divided in two sections, one covering content-independent noise types such as **Additive White Gaussian Noise** (AWGN) and **Random Impulse Noise** (RIN). The second section covers content-dependant noise types such as **Motion Blurring Noise** (Blur) and **JPEG Compression Artifacts** (JPEG). For each of these types of noise a dedicated "expert system" was developed to determine the intensity of that specific type of noise. The first category, considering content-independent noises, a kind of "unity" measure was then developed. In order to consider one "unit" of AWGN as being equal to one "unit" of RIN, an objective Image Quality Metric (IQM) was used to establish this equivalence. This IQM was developed at the University of Texas and is called "SSIM". Thus, using this SSIM an equivalence table was generated using several images, each applied with different intensities of either AWGN or RIN. In this way a certain intensity α of AWGN can be considered to be as corruptive as an intensity β of RIN. Then two algorithms were implemented each specialized in detecting one specific type of feature in an image. **The first** was developed by J.S. Lee and K. Hoppel titled "Noise Modeling and Estimation" used for determine the parameters of Additive White Gaussian Noise in an image. A software implementation of the algorithm was developed. Then a second expert system was developed, specialized in detecting Random Impulse Noise. The algorithm, developed by myself, consists of sweeping a horizontal edged detector over the image then a vertical edge detector is applied. Then a logical 'OR' is executed using the horizontal and vertical edge maps as inputs. What will appear on this "OrEdgeMap" are odd looking artifacts or donut-shaped rings encircling the pixel location where impulse noise was present in the original image. Then a series of masks are swept over the OrEdgeMap to pinpoint the locations of these donut rings. All of these locations are tabulated into a FlagMap. A final thresholding stage must be done to this FlagMap. It was empirically found that pixels that were flagged 5 times or more are almost certain to be corrupted by impulse noise. Then, using these two algorithms to determine the intensity of first AWGN and then the intensity of RIN in an image, both intensities are then compared to the lookup table, developed offline in the first part. The noise with the highest intensity on the unit-scale is considered, in a first place, to be dominant for content-independent noise. Then a similar process was developed for content-dependant noise types. However for content-dependant noise, the noises couldn't directly be compared to each other by using an equivalence table. In the case of blurring noise, an image is more susceptible when it contains many edges and has complex patterns, whereas a smooth image of a sky will be less susceptible to blurring noise. Conversely for JPEG noise, an image with complex patterns will mask any JPEG artifacts and these will become less visible, however an image with little or no edges will not mask or hide any JPEG artifacts therefore JPEG block artifacts will be much more visible in an image with a large surface of a smooth gradient such as a sky. Therefore using the same Image Quality Metric, the SSIM, as in the content-independent phase to create a "noise equivalence" table however for content-dependent noise such as blurring, five noise intensity equivalence tables are created. The differentiating factor between these tables is the Edge-count of the test image after an edge detector has been passed over the image. So table 1 is used when it is considered to be few edges in an image, and table 5 is used when there are many edges in the test image. As a result a preprocessing phase must be executed on the image to determine the edge count in order to use the appropriate table 1 through 5. **A third** "expert system", dedicated to determining the intensity of blurring noise is applied to the image. This algorithm I've also developed uses an edge detector. By rotating the image slightly prior to applying the edge detector we obtain an angular edge graph, from this graph we must extract the position with the largest difference in edge count between an angle and its perpendicular angle. That will be considered to the shifting angle. Afterwards, to determine the pixel displacement of the blurring noise, a Richardson-Lucy deconvolution is used. With this algorithm determines the intensity of the motion blurring noise in an image. **The fourth** specialized modular "expert" developed for the system was a way to detect JPEG noise. The algorithm consisted of sweeping an edge detector over the image and then adding up all the edge information contained at a 'block boundary'. Then doing the same at a pixel row that is just one row above the block boundary or one row below the boundary. Then subsequently repeating this for several threshold values of the edge detector. Then the cumulative statistical data at the block boundary is compared to the cumulative data at the pixel row immediately above or below the block pixel. Finally, the noise intensity equivalent tables of the content-independent noise from the first part is compared to the table of the content-dependant noise that was used respective to the edge count in the second part, and the final winner is then determined.