A Fast Wavelet-Based Algorithm for Global and Local Image Sharpness Estimation

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Abstract—In this paper, we present a simple, yet effective
wavelet-based algorithm for estimating both global and local
image sharpness (FISH, Fast Image Sharpness). FISH operates
by first decomposing the input image via a three-level separable
discrete wavelet transform (DWT). Next, the log-energies of the
DWT subbands are computed. Finally, a scalar index correspond-
ing to the image's overall sharpness is computed via a weighted
average of these log-energies. Testing on several image databases
demonstrates that, despite its simplicity, FISH is competitive
with the currently best-performing techniques both for sharpness
estimation and for no-reference image quality assessment.

I. INTRODUCTION

A useful goal in image processing is to determine whether
one image (region) appears sharper than another. Algorithms
which can automatically predict perceived sharpness or blur-
riness are known as sharpness estimators or blurriness es-
timators, respectively. Such algorithms have been shown to
be useful for tasks such as main-subject detection, image
quality assessment, and image restoration (see [1] for relevant
references).

Previous methods of sharpness/blurriness estimation have
employed a wide variety of approaches [2], [3], [4], [6]. The
vast majority of these methods operate under the assumption
that the appearance of edges is affected by blur, and accord-
dingly these methods estimate sharpness/blurriness by using
various edge-appearance models. For example, Ferzli et al. [3]
measure edge widths in $8 \times 8$ blocks, which are then weighted
by a Mean Just-Noticeable Blur factor (see also [4]). Liu et
al. [5] employ edge features extracted by using a Sobel edge
detector, and then combine these features via a circular back-
propagation neural network system for blur estimation. Li et
al. [6] compare the kurtoses of blocks of dominant edge pixels
in the input image with those of a purposely re-blurred version.

Other methods have used spectral information to estimate
sharpness [7], [8], [9]. For example, Shaked et al. [7] use the
DFT to estimate sharpness based on the ratio of high-
pass to low-pass energy of the the spatial derivative of each
line/column. Sharpness has also been estimated based on the
peakedness of the energy spectrum [8], and on the uniformity
of the energy spectrum [9].

Various DCT, DWT, and other transforms have also been
used either to detect edges and/or to model edge-appearance.

Sharpness/blurriness has been estimated based on the kurtosis
of DWT coefficients corresponding to edge blocks [10], based
on the Lipschitz exponent of the sharpest edges [11], based on
edge types [12], and based on local phase coherence measured
via complex wavelets [13].

More recently, hybrid approaches have been developed
which employ a combination of edge-/pixel-based and
transform-based methods [14], [1]. For example, Chen et al.
[14] proposed a blur metric that employs the statistics of the
image gradient histogram and a wavelet-based detail map. Vu
et al. [1] used a block-based approach to develop the first
method specifically designed to measure local sharpness. Their
method estimates the spatial and spectral sharpness of local
image regions using the slope of the local magnitude spectrum
and the local total variation; these values are then combined
to generate an image sharpness map. Hybrid approaches have
generally proven to perform better than edge-only based or
transform-only based methods, though at the expense of added
computational complexity.

In this paper, we present a sharpness estimator, called
FISH (Fast Image Sharpness), which offers the simplicity
of a spectral-based method but with the improved predictive
performance of a hybrid method. Following from [7] and [8],
FISH operates under the assumption that perceived sharpness
can be estimated by examining the energy in high-frequency
bands. Here, we use a three-level separable discrete wavelet
transform (DWT) and measure the log-energy of the DWT
subbands. Sharpness is estimated based on a weighted geo-
metric mean of these log-energies. As we will demonstrate,
despite its simplicity, FISH is competitive with the currently
best-performing techniques. In addition, by clustering DWT
coefficients, we show how FISH can be easily modified to
yield a map indicating the relative sharpness of each image
region. Thus, unlike most existing methods (with the exception
of [1]), FISH can generate sharpness maps.

This paper is organized as follows: In Section II, we provide
details of the FISH algorithm. Section III presents results of
FISH on within-image and across-image sharpness estimation,
and on no-reference quality assessment of blurred images; this
section also includes a discussion of runtime requirements.
General conclusions are presented in Section IV.
II. ALGORITHM

A. Global Image-Based FISH

Given a grayscale input image \( I \), the FISH algorithm consists of the following three steps:

1) \textit{Step 1: Compute the DWT:} The grayscale input image is decomposed into wavelet subbands by using the Cohen-Daubechies-Fourier 9/7 filters [15] with three levels of decomposition. Let \( S_{LH}, S_{HL}, S_{HH} \) denote the LH, HL, and HH subbands at DWT level \( n \in [1, 3] \). (The \( L_3 \) subband is not used.)

2) \textit{Step 2: Compute the Log-Energy at each DWT Level:} Images which appear sharp generally contain more high-frequency content than images which appear smooth/blurred. To quantify this effect, we first measure the log-energy of each subband at each decomposition level as follows:

\[
E_{XY} = \log_{10}(1 + \frac{1}{N_n} \sum_{i,j} S_{XY}^2(i,j)),
\]

where \( XY \) is either \( LH \), \( HL \) or \( HH \). The quantity \( N_n \) is the number of DWT coefficients in the subband at level \( n \). The addition of one is used to prevent negative values of \( E_{XY} \).

Next, we measure the total log-energy at each decomposition level via

\[
E_n = (1 - \alpha)\frac{E_{LH} + E_{HL}}{2} + \alpha E_{HH},
\]

where the parameter \( \alpha = 0.8 \) was chosen empirically to give greater weight to the energy in the HH subband; this band can be regarded to span a higher radial spatial frequency (by a factor of \( \sqrt{2} \)) than the LH and HL bands.

3) \textit{Step 3: Compute the Sharpness Index:} Finally, the three per-level log-energy values \( E_1, E_2, \) and \( E_3 \) are combined as follows to determine a scalar sharpness index representing the image’s overall sharpness:

\[
\text{FISH} = \sum_{n=1}^{3} 2^{3-n} E_n,
\]

Here, FISH \( \geq 0 \), is the overall sharpness index; the larger the index, the greater the perceived sharpness. The factor \( 2^{3-n} = \{4, 2, 1\} \) when \( n = \{1, 2, 3\} \) is used to provide greater weight to the finer scales (higher-frequency bands).

B. Local Block-Based FISH

The previous section described the FISH algorithm applied to the entire image. It is also possible to apply the algorithm in a block-based fashion to determine a map denoting local perceived sharpness.

To generate the sharpness map, we compute a collection of local FISH values using the DWT coefficients corresponding to each 16 \( \times \) 16 block of the image. Following the procedure described in [16], each subband is divided into small blocks of size 8 \( \times \) 8, 4 \( \times \) 4, and 2 \( \times \) 2 for levels 1, 2, and 3, respectively. As shown in Figure 1, the 16 \( \times \) 16 DWT coefficients corresponding to the top-left 16 \( \times \) 16 block of the image are assembled by taking three 8 \( \times \) 8 blocks from the level-1 bands, three 4 \( \times \) 4 blocks from the level-2 bands, and three 2 \( \times \) 2 blocks from the level-3 bands. Equation (3) is then applied to these 16 \( \times \) 16 coefficients to compute a FISH index for this top-left block.

This process is repeated for each 16 \( \times \) 16 block with 50% overlap between two consecutive blocks of DWT coefficients to generate a sharpness map. Because we use 50% of overlap between neighboring blocks, each pixel in the sharpness maps corresponds to a block size of 8 \( \times \) 8 in the input image. Figure 1 (right) illustrates the sharpness map of the image \( \text{lena} \).

It is also possible to collapse the sharpness map into a scalar sharpness index representing the image’s overall sharpness. This index, FISH \( \text{bb} \), is computed by taking the root mean square of 1% largest values of local sharpness (FISH) indices (following from [1]):

\[
\text{FISH}_{\text{bb}} = \sqrt{\frac{1}{T} \sum_{i=1}^{T} \text{FISH}_i^2},
\]

where \( T \) denotes the number of blocks which received the 1% largest FISH indices of the sharpness map; and where FISH\( _i \), \( i = 1, 2, \ldots, T \) denotes the FISH indices of these blocks. The value of 1% is used because, as argued in [1], the overall perceived sharpness of an image is largely determined by the image’s sharpest regions.

III. RESULTS AND DISCUSSION

A. Representative Results

Figure 2 shows representative results that demonstrate the ability of FISH/FISH\( \text{bb} \) to accurately estimate across-image and within-image sharpness (FISH\( \text{bb} \) only) for a variety of images containing different sharpness levels. The images are ordered based on subjective ratings of sharpness [1].

In terms of across-image sharpness, the FISH/FISH\( \text{bb} \) indices generally match the relative perceived sharpness across these images. For example, two of the images, \textit{petal} and \textit{zebra}, are not as sharp as images \textit{pelicans} and \textit{branches}, but are clearly much sharper than image \textit{ball}. Both FISH and FISH\( \text{bb} \) fail to predict the sharpness of image \textit{petal} in comparison to either image \textit{airplane} (for FISH) or image \textit{zebra} (for FISH\( \text{bb} \)). We believe that these failure cases are attributable to the fact...
neither FISH nor FISH\textsubscript{bb} take into account local contrast. Such a measurement could be implemented, though at the expense of added complexity.

In terms of within-image sharpness, FISH\textsubscript{bb} correctly estimates the perceived sharpness of each image region. For example, in image petal, the the flower’s stamens and the edges of the petals are the sharpest regions in this image; these regions are accurately highlighted in the corresponding FISH\textsubscript{bb} map. Similarly, in image branches, the branches are much sharper than the sky; this fact is reflected in the corresponding FISH\textsubscript{bb} map.

### B. No-Reference Quality Assessment of Blurred Images

To evaluate the performance of FISH on no-reference quality assessment of blurred images, we used the blurred image subsets from four image-quality databases: (1) The LIVE database [17] (containing 145 blurred images); (2) the IVC database [18] (20 blurred images); (3) the TID database [19] (96 blurred images); and (4) the CSIQ database [20] (150 blurred images). We compared our method against seven other sharpness/blurriness/quality estimators for which code is publicly available: MMZ [21], MDWE [2], ST [7], JNBM [3], CPBD [4], BLINDS-II [22], and S\textsubscript{3} [1]. The performance of predicting subjective ratings of quality was measured in terms of the Spearman rank-order correlation coefficient (SROCC) for gauging prediction monotonicity; the Pearson linear correlation coefficient (CC) (following non-linear regression; see [1]) for gauging prediction consistency; and the outlier ratio (OR) and outlier distance (OD) [20] for outlier analysis.

Table I shows the results of this evaluation. Both FISH and FISH\textsubscript{bb} perform quite well on all four databases. In terms of CC and SROCC, FISH\textsubscript{bb} outperforms other methods on the two largest databases (CSIQ and LIVE2) and is competitive on the other two databases; FISH and MMZ are the two best methods on IVC. In terms of outliers analysis, FISH\textsubscript{bb} also shows the best performance.

### C. Local Sharpness Estimation

We compared the sharpness maps from FISH\textsubscript{bb} with ground-truth sharpness maps obtained from human subjects [1]. Figure 3 shows three original images and the corresponding sharpness maps obtained from human subjects and estimated by S\textsubscript{3} and FISH\textsubscript{bb}. The S\textsubscript{3} algorithm was specifically designed to generate sharpness maps and was shown in [1] to generally yield the best map predictions. As shown in Figure 3, FISH\textsubscript{bb} can yield maps which are quite competitive with S\textsubscript{3}’s maps. This latter assertion is quantified in Table II, which shows the SROCC, CC (after non-linear regression), and RMSE between the ground-truth sharpness maps and the maps predicted via S\textsubscript{3} and FISH\textsubscript{bb}.
D. Runtime vs. Image Size

To evaluate runtime, we applied FISH, FISHbb, and other sharpness/blurriness estimators to images of size 512 × 512, 1024 × 768, 1280 × 960, and 1600 × 1200 pixels. Table III shows the average runtime of each algorithm in seconds, where the average was taken over 100 trials. This test was performed using a modern desktop computer (Intel Quad Core at 2.66 GHz, 12 GB RAM DDR2 at 6400 MHz, Windows 7 Pro 64-bit, Matlab 7.8). All of the methods were implemented in Matlab.

As shown in Table III, FISH is the fastest algorithm for all image sizes, and FISHbb is still significantly faster than the methods which yield competitive predictive performance (S3, JNBM, CPBD, and BLIINDS-II; see Table I). In terms of memory requirements, both FISH and FISHbb have the same memory requirements as a standard DWT with only a negligible amount of additional memory needed for the output map (for FISHbb) and other scalar variables.

IV. CONCLUSIONS

This paper presented a simple, yet effective algorithm (FISH) for estimating both global and local image sharpness. FISH operates by first decomposing the input image via a three-level separable DWT, and then estimating sharpness based on a weighted geometric mean of the DWT subband energies. To generate a local sharpness map, FISH can be operated in a block-based fashion (FISHbb) by applying the same computation to groups of DWT coefficients. We demonstrated the efficacy of FISH/FISHbb on several image databases.

REFERENCES


