Variance Ranklets: orientation–selective rank features for contrast modulations

George Azzopardi
http://www.cs.rug.nl/~george

Department of Mathematics and Computing Science
University of Groningen
Groningen, Netherlands

Fabrizio Smeraldi
http://www.dcs.qmul.ac.uk/~fabri

School of Electronic Engineering
and Computer Science
Queen Mary University of London, UK

Rank features are arguably the most robust kind of descriptors available to Computer Vision practitioners, being invariant to all monotonic brightness transformations. Orientation selectivity has recently been introduced to rank features by Ranklets [3]. Designed in close analogy with Haar wavelets, Ranklets are based on the Wilcoxon statistics and have a simple interpretation in terms of the pairwise comparison of pixel intensity values.

Orientation selectivity is a key feature of widely used linear features such as Gabor filters, that are accepted as a model of low-level human vision, namely of the response of simple cells in the primary visual cortex. Linear filters are a natural choice to model sensitivity to intensity modulations (so called first–order stimuli), to which also Ranklets respond. The human visual system, however, also shows a similar response to contrast or variance modulations (second–order stimuli - Fig. 2a); these are thought to be important, for instance, in the perception and discrimination of textures. Contrary to first–order stimuli, the response to second–order stimuli is not easily modelled by linear filters. Perhaps the most common approach in the psycho-physical literature is the linear-nonlinear-linear (LNL) model, that consists of two linear filter stages separated by a non-linearity stage [1]; indeed, features designed for second–order stimuli are rare in the applied literature.

We present what we believe is the first set of rank features for the orientation selective detection of second–order stimuli. Variance Ranklets are defined in analogy with Ranklets, using the Siegel-Tukey statistics for dispersion instead of the Wilcoxon statistics for translation. Both statistics are computable with a sorting operation and a sum and have the same null distribution, leading to a uniform treatment of information from first– and second–order stimuli. Variance Ranklets present the same pattern of orientation selectivity that characterises standard (intensity) Ranklets and Haar wavelets.

Ranklets apply the Wilcoxon test to compare pixels in two neighbouring image regions based on the relative order of their intensity values rather than on their absolute intensity. In accordance with the statistical literature, we denote the pixels in the two regions as the Treatment and Control samples T and C; their geometric arrangement on the image determines the orientation–selective behaviour of the filters. The samples are defined based on the three Haar wavelets $h_i(\vec{x}), i = 1,2,3$ supported on a given local window W, as sketched in Fig. 1. The counter–images of $+1$ and -1 under these three functions provide three choices for T and C, namely $\mathsf{T}_i = h_i^{-1}(\{+1\})$ and $\mathsf{C}_i = h_j^{-1}(\{-1\})$. As said, pixels in the T and C sets are sorted and their intensity values replaced by their rank, assigned in increasing order for the Wilcoxon test against translation. For example, for 4 Treatment and 4 Control observations corresponding to intensity values $\mathsf{T} = \{64,128,12,56\}$ and $\mathsf{C} = \{10,75,25,100\}$ we have (Wilcoxon ranks):

Intensity	10	12	25	56	64	75	100	128
Sample	C	T	C	T	T	C	C	T
Wilcoxon rank	1	2	3	4	5	6	7	8
Siegel–Tukey rank	1	4	5	8	7	6	3	2

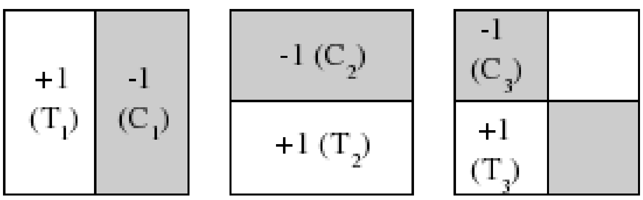
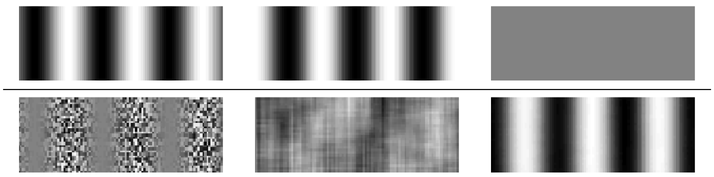


Figure 1: The "Treatment" and "Control" pixel sets defined by the three Haar wavelets $h_1(\vec{x})$, $h_2(\vec{x})$ and $h_3(\vec{x})$ (from left to right).



(a) (b) (c)

Figure 2: (a) First–Order (top) and Second–Order (bottom) sinusoidal modulations characterised by local variations in luminance and contrast respectively; (b) response of a standard (Intensity) Ranklet on the signals in (a); (c) response of our proposed Variance Ranklet (vertical orientation, filter size matched to wavelength of stimulus).

However, if we are interested in testing against the alternative that the pixels in T differ from the pixels in C in *variability*, we can assign ranks as specified in the last row above (Siegel–Tukey ranks). The sum of the treatment ranks, $ST = 4+8+7+2$, is in this case known as the Siegel–Tukey statistics [2]. Clearly, high values of the statistics indicate that the observations in the T set are grouped more tightly around their median than those in the C set. Thus the Siegel–Tukey statistics can be used to test the data for spread, under the assumption that the two samples are drawn from distributions with equal median. Computing the Siegel–Tukey statistics ST^i on the three choices of T_i and C_i determined by the Haar orientation in Fig. 1 leads to the three variance Ranklets

$$R^i_{ST} = 2ST^i_{YX}/n^2 - 1, \tag{1}$$

where n is the number of pixels in T_i and $ST^i_{YX} = ST^i - (n+1)n/2$. Our definition closely follows that of Ranklets [3]. The response of a Variance Ranklet varies between -1 and $+1$, with the extremes indicating that the intensities of all the pixels in the T set are more tightly grouped around their median than those in the C set $(+1)$, or vice-versa for (-1).

Fig. 2(c) shows the response of a Variance Ranklet tuned to the vertical orientation on both first– and second–order sinusoidal stimuli. As can be seen, the filter responds selectively to variance modulations that are invisible to the corresponding (intensity) Ranklet (or to a linear filter such as a Haar wavelet).

In the paper we give a more detailed description of our features and of the relevant statistical background, and we present a sample application to texture classification using a subset of the standard VisTex and Brodatz databases. Starting from the responses of intensity and Variance Ranklets, we compute the statistical descriptors described in [4] and classify the resulting feature vectors with a simple Nearest Neighbour classifier. Our experiments show that the use of Variance Ranklets together with intensity Ranklets significantly improves classification accuracy with respect to standard Ranklets alone. Comparison with recently published results on the same datasets confirms that the low error rates achieved by our approach are in line with the state of the art.

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