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Ranklets: A Qualitative Review

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***Abstract*-This paper reviews Ranklets, a family of multiscale, orientation-selective , non-parametric features modeled on Haar wavelets. Ranklets are related to wavelets and rank statistics. At the inception, a basic discussion on Ranklets is presented here. Next a focus is given to the various algorithms used so far to compute Ranklets with their complexities. The different applications of Ranklets in the field of face detection, point tracking, breast cancer, and texture classification have been thoroughly surveyed to analyze the strength and beauty of the Ranklet transform in advanced imaging. Finally a special effort is undertaken to mark a few novel papers to guide the future works.**

Keywords: Haar Wavelets, Quicksort, Hidden Markov Tree, Support Vector Machine.

I. Introduction

Over the years, wavelets, a time-tested successful tool for signal analysis, have replaced the Fourier Transform as an alternative approach to the time and frequency resolution problem [40]. Although resolution problems are inherent due to the physical phenomenon (Hiesenberg's Uncertainty Principle), wavelets have yielded more than satisfactory results to this problem. But one of the disadvantages of wavelets is that it is not immune to the monotonic transformations of the image such as gamma correction and histogram equalization. This poses a problem in areas where monotonic transformations are an indispensible part of the process, such as face detection. This problem is solved in [1] by incorporating rank statistical features to wavelets. Rank Statistics rely on the relative order (rank) of the measurements, such as gray-level intensities, rather than on their specific values. So they are non-parametric, meaning that they circumvent the problem of making assumptions about the underlying distribution of data, and hence are invariant to the monotonic transformations of images. The above amalgamation of wavelets and rank statistics yield the Ranklet transform. In section II, we define and discuss the various salient features of Ranklet transform. Section III deals with the various algorithms of Ranklets. Then in Section IV we discuss the various applications of Ranklets. Section V deals with ten most influential papers on Ranklet transforms.

II. Definition and salient features of Ranklet transform

Ranklet transform is a family of multiscale, orientation-selective, non-parametric features based on Haar wavelets. Given a set of (x_1, x_2, ..., x_N) pixels, the rank transform substitutes each pixel's intensity value with its relative order i.e. rank among all the other pixels. The rank transform is a nonparametric transform since, given an image with N pixels, it replaces the value of each pixel with the value of its order among all the other pixels. Ranklets are designed starting from the three 2D Haar wavelets and the rank transform. Haar wavelets [12], introduced in 1909 by Alfrėd Haar, are the simplest possible wavelets. In analogy to the wavelet transform, ranklet coefficients can be computed at different orientations by applying vertical, horizontal and diagonal Haar wavelet, as shown in Fig 1, supports to each image under analysis. As a result, the orientation selectivity feature of the ranklet representation follows. The close correspondence between the Haar wavelet transform and the ranklet transform leads directly to the extension of the latter to its multiresolution formulation. This means that, as for the wavelet transform, it is possible to compute the ranklet transform of an image at different resolutions by means of a suitable stretch and shift of the Haar wavelet supports. At the same time, for each resolution, it is possible to characterize the image by means of orientation selective features such as the vertical, horizontal and diagonal ranklet coefficients. The multiresolution ranklet transform of an image is thus a set of triplets of vertical, horizontal and diagonal ranklet coefficients, each one corresponding to a specific stretch and shift of the Haar wavelet supports.

The ranklet transform is obtained in two steps. In the first step the N pixels are split into two subsets T and C of size $N/2$, thus assigning half of the pixels to the subset T and half to the subset C. The two subsets T and C are defined being inspired by the Haar wavelet supports depicted in Fig. 1. In particular, for the vertical Haar wavelet support, the two subsets T_1 and C_1 are defined; similarly for the horizontal and diagonal ones. The definition of the afore mentioned Haar wavelet supports forms the basis for the orientation-selective characteristic of the ranklet transform

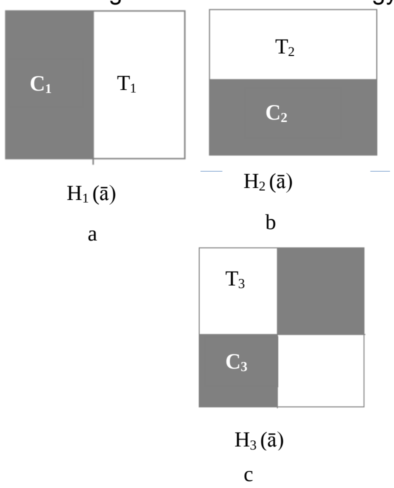

Fig 1. The three Haar wavelets,(a) H_1(ā) (vertical orientation); (b) H_2 (ā) (horizontal orientation); (c) H_3 (ā) (diagonal orientation)

The second step consists in computing and normalizing in the range [-1, +1] the number of pixel pairs (p_m, p_n), with $p_m \in$ T and $p_n \in$ C, such that the intensity value of p_m is higher than the intensity value of p_n. This is done for each orientation, namely vertical, horizontal and diagonal. The geometric interpretation of the so-called ranklet coefficient R_j where j denotes the orientation, is quite straightforward. Suppose that the image we are dealing with is characterized by a vertical edge, with the darker side on the left, where C_1 is located, and the brighter side on the right where T_1 is located as shown in Fig 1(a). R_1 will be close to +1 as many pixels in T_1 will have higher intensity values than the pixels in C_1. Conversely, R_1 will be close to -1 if the dark and bright side are reversed. Horizontal edges or other patterns with no global left-right variation of intensity will give a value close to 0. Analogous considerations can be drawn for the other ranklet coefficients, R_2 and R_3. The use of the pixels' ranks, rather than their intensities, forms the basis for the non-parametric characteristic of the ranklet transform. Due to this robust features of ranklets, they have been applied to face detection [1, 9, 7], point tracking [3, 5], digital mammography [3, 8], and texture classification [4, 10] and so on.

III. Performance Analysis of the Computational Algorithms

Ranklet transform of an image is obtained by first evaluating its co-efficients. The co-efficients can be calculated using different algorithms as shown in Fig [2] [11]:

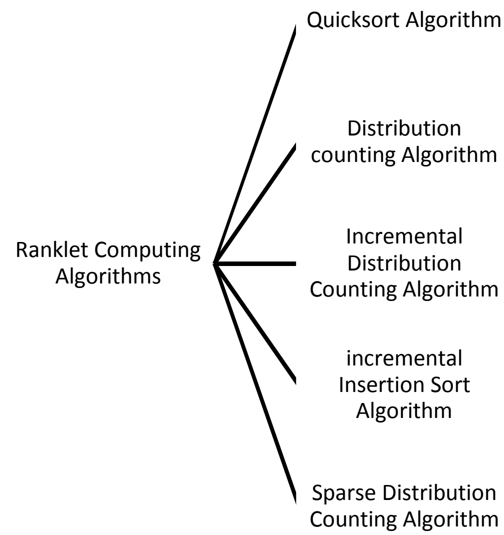

Fig 2. The different ranklet computing algorithms

*A. Quicksort Algorithm (QS)***:**It is the most widely used algorithm for the computation of the Wilcoxon statistics in order determine the Ranklet co-efficients. It has a complexity of *O (NlogN),* where N is the number of pixels, and O denotes the complexity. While the complexity of QS is relatively low, it has hindered the application to real-time or high-throughput image analysis. Thus the alternative faster algorithms have been introduced.

B. Distribution Counting Algorithm (DC): The demerits of the above mentioned algorithm is overcome to some extent by the Distribution Counting algorithm. Due to the quantized nature of image brightness, the DC algorithm [11] can be use to compute Ranklets with linear complexity.The DC algorithm sorts by accumulation, which is a more efficient strategy in the case of limited or quantized set of values such as pixel intensities. The complexity of this algorithm is O (N + ℓ), where ℓ is the number of grey levels.

C. Incremental Distribution Counting Algorithm (IDC): When the same filter is to be applied to the entire image, some optimizations in the speed of the algorithm is possible leading to the Incremental Distribution Counting algorithm. This algorithm achieves considerable computational savings in time by exploiting the almost complete overlap between two consecutive positions of the support window W as it scans the image. One only needs to maintain the histogram H_w of W together with the histogram $H_{Ti,}$ of the T_i for each of the three orientations. When W is slid one pixel to the right, the histograms can be efficiently updated as shown in Fig 3. The histogram updates involve only two full columns of W.

Therefore for a square window, the entire decomposition can be computed at a cost of O $(2\sqrt{N} + \ell^*)$ per Ranklet, where ℓ^* is the average range of gray levels appearing in W. This algorithm presents a considerable improvement in speed over the QS.

D. Incremental Insertion Sort Algorithm (IIS): This algorithm has a very simple structure that makes it very efficient for small set of points. It is more efficient on partially ordered arrays. In this algorithm an update similar to the IDC, is applied, hence the name Incremental Insertion Sort algorithm. The time complexity of this algorithm is O $(N + d)$, where d is the number of inversions.

E. Sparse Distribution Counting Algorithm (SDC): When Ranklets with different support windows must be computed at sparse image locations, a catching mechanism is the SDC algorithm. The previous algorithms cannot be utilized, since when locations are sparse it is no longer possible to exploit window overlap to increase the efficiency. SDC requires a preprocessing step that is linear in the number of pixels of the entire image, but then allows computing ranklets of any size with a linear complexity of O $(\sqrt{N})$, where $\sqrt{N}$ is the *y* size(vertical size) of W.

Evaluating the comparative performance of Quicksort, Incremental Distribution and the Incremental Insertion Sort, it is found that the IDC algorithm is by far the best choice among the three algorithms, outperforming the others for most of the window sizes. Comparing the Distribution Counting, Sparse Distribution Counting and Quicksort, it is seen that SDC and DC outperform QS. The linear dependence of SDC on the vertical size of the support window W makes it faster for large window sizes. But up to window sizes of 350 X 350 pixels, DC is preferred, as it does not require a preprocessing step. By far, the best algorithm is the SDC algorithm, followed by the IDC algorithm. For small images, the DC algorithm is most suitable.

The algorithms discussed above achieve considerable speedups, providing options other than the conventional procedures.

IV. Applications of Ranklets

The novel features of Ranklets have been successfully implemented in different avenues of imaging such as face detection [1, 9, 7], point tracking [3, 5], digital mammography [3, 8, 26], and texture classification [4, 10]. The applications are hereby discussed.

A. Face detection: One of the most successful applications of image analysis and understanding is face recognition and verification. The face is one of the several features that can be used to uniquely identify a person. No two human faces are identical, which makes them well suited for use in identification schemes. The applications for robust automated face detection are in workstation security, accesses control to building, banking operations and archives [34]. Ranklets have been used in face recognition systems where they have outperformed a wide range of other algorithms [1] including the Haar Wavelets, SNoW and linear Support Vector Machines (SVM), that implemented in face detection earlier. In [9], a hybrid method involving the Hidden Markov Tree (HMT) and the Ranklet transform have been introduced as a new technique in face detection. The HMT model was introduced by Crouse, Nowak and Baraniuk in [33] for modeling nonindependent, non-Gaussian wavelet transform coefficients, where the model has been successfully used in image denoising and segmentation. The combination of the powerfulness of HMT as a modeling tool and the robustness of the Ranklet transforms as features, as shown in Fig 3. has introduc-ed a new reliable face verification and recognition system.

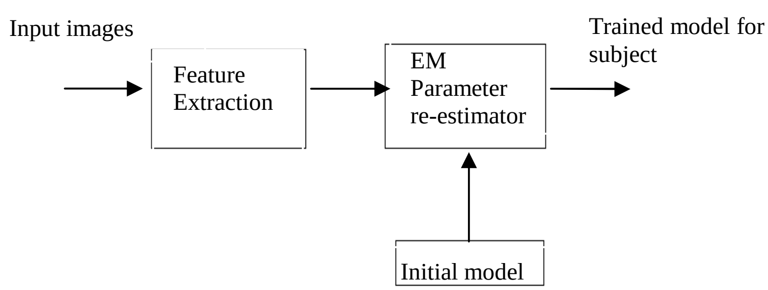

Fig 3(a). Ablock diagram for the training phase of the HMT + Ranklet system

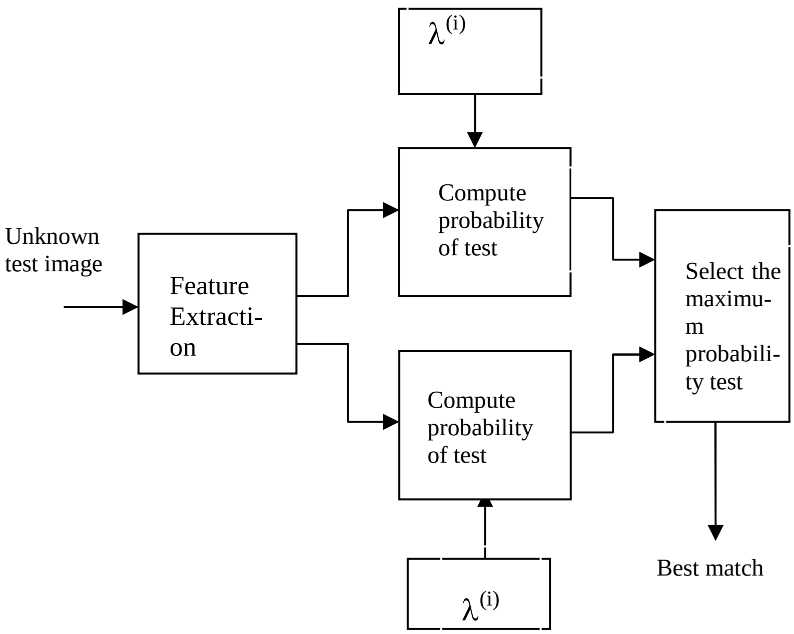

Fig 3(b). A block diagram of the recognition phase of the HMT + Ranklet system

*B. Tracking points***:** The difficulty in point tracking arises not from the necessity of locating the tracking targets precisely, but also allocating the appearance variation of the tracked objects [5, 14, 16]. The introduction of Ranklet transform to point tracking algorithm has introduced a high degree of invariance to the illumination and appearance changes resulting from 3D rotations and deformations of the object. The orientation selectivity of ranklets adds to the discriminative power of the representation, thus minimizing point drift. The tracking algorithm incorporating Ranklet transform has showed its ability to handle the deformations and pose changes of a non-rigid object.

C.Texture classification: Texture is a surface property which gives combined information on the smoothness, coarseness, and regularity of objects. In digital images, it is reflected as local variations of the gray-scale content. Texture classification has several applications in biomedical imaging, remote sensing, image classification and segmentation [3, 23, 25]. Application of the Ranklet transform in texture classification along with SVM classifier [4], as shown in Fig 4, has extended its robust features to the process. The non-parametric property of Ranklets allows production of gray-scale invariant image representation. Orientation-selectivity of Ranklets makes the process invariant to 90^o variations. Also this transform allows to recognize analogous characteristics at different resolutions and orientations of the image. As a result, texture classification using Ranklet transform outperforms the previous methods employed for the job. Also a novel type of rank features, Variance Ranklets, which uses Siegel-Tukey Statistics instead of Wilcoxon Statistics [10], has shown orientation-selectivity on contrast or variance of Variance Ranklets along with Intensity

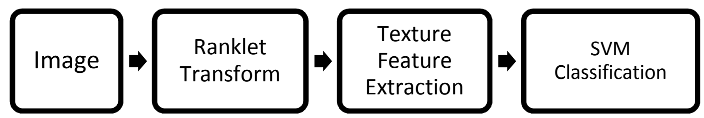

Fig 4. Texture Classification using ranklets and SVM classifier [4].

Ranklets greatly improves texture classification, and is the first family of rank filters designed to detect orientation in variance modulations.

D. Digital Mammography: Breast cancer accounts for a high percentage of cancer incidence in women, approximately 32% of all cancer cases. The abnormalities associated with the carcinoma of breast are tumoral mass-thickening of the breast tissue, calcifications, dilated lactiferous ducts, focal areas of asymmetry or architectural distortion, and thickening or retraction of the skin . While trying to detect breast cancers at an early stage using X-ray screening, the radiologists may miss 15-30% of the breast lesions. Computer Aided Detection (CAD) systems aims to increase the efficiency and effectiveness of screening procedures by using the computer system as a second reader [35, 37]. A novel approach to the detection of masses and clustered microcalcifications is presented in [3], using ranklet transform as shown in Fig 5. In this method, the image is codified by using a ranklet transform in order to get an effective and stable representation. The vectors of ranklet coefficients obtained are classified by means of an SVM classifier. This approach has two advantages. First it does not need any feature selected by the trainer. Second, it is quite stable, with respect to the image histogram. That allows us to tune the detection parameters in one database and use the trained CAD on other databases without needing any adjustment. Two separate algorithms, one for detecting masses and another for detecting microcalcifications are used.

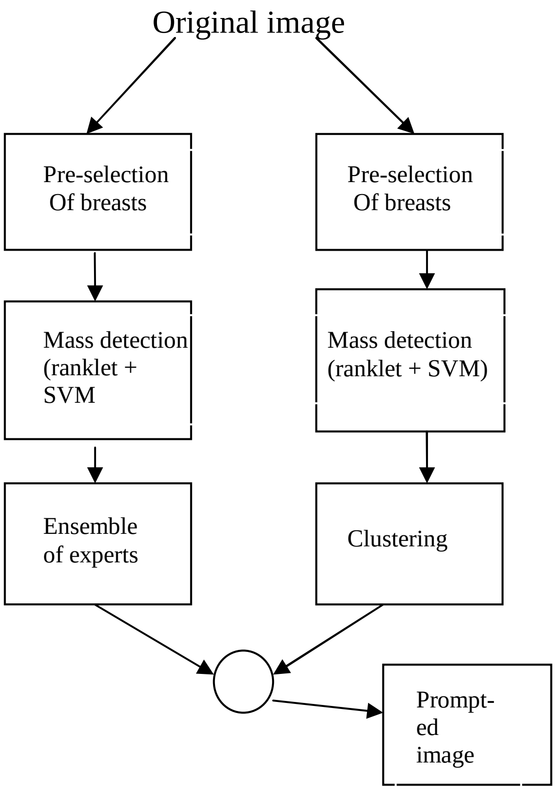

Fig 5. Chart of a Ranklet-based detection scheme

In the process discussed above a great amount of ranklet coefficients are generated. In order to reduce the amount of ranklet coefficients arising from the ranklet transform of each image, a feature reduction technique, known as Recursive Feature Elimination (RFE), is applied in [8]. RFE is a general method for eliminating features which are responsible of small changes in the classifier's cost function. The process is iterated until a reasonable small number of features survive, or the performance of the classifier starts degrading.

The application of ranklets in digital mammography has been effective [38], giving high sensitive values (true positive-values) when classifying tumoral masses, while reducing the number of false–negatives. Moreover, ranklets are used to represent images for determining the Region of Interests (ROI) in mammography, before presenting the images to SVM.

V.Conclusion

To conclude this paper, we have selected seven papers, that are 'must read' papers for anyone interested in ranklets. These papers are not claimed to be the 'best' but they give a very basic and clear idea about ranklets.

A. F.Smeraldi (2002) [1]: The paper that introduced ranklets, this paper is where the study of ranklets begins.

B. F.Smeraldi & Mohammed A.Rob [7]: This paper generalizes ranklets to hexagonal pixels, thus extending the possibility of using ranklets in CCD technology.

C. F.Smeraldi et al.(2005) [2]: This paper implements the robust nature of anklets in tracking points on deformable objects.

Fig 5. Chart of a Ranklet-based detection scheme

D. Mahmoud A. Ismail and Reda A. El-Khoribi (2006) [9]: It introduces the Hidden Markov Tree of the ranklet transform as a new recognition and verification system and the evaluation of the procedure.

E. F.Smeraldi (2009) [11]: The different algorithms that can be used to compute ranklets along with the complexity of each is given. It is very helpful for selection of the correct algorithm while implementing ranklets.

F. M.Masotti & Renato Campanini (2008) [4]: Introduces ranklets in the texture classification domain, and demonstrates the utility of the robust features of ranklets in this field.

G. George Azzopardi & F.Smeraldi (2009) [10]: Presents the first set of rank features for the orientation selective detection of second-order stimuli viz. contrast modulation by substituting Siegel-Turkey statistics instead of Wilcoxon statistics, and its application to texture classification.

The multiscale, orientation-selective, non-parametric Ranklet transform has already proved its mettle in the field of Image Processing. The generalization of Ranklets to hexagonal pixels [7], with recent advances in CCD technology has opened up new horizons in the field. The hybridization of Ranklets with new global search techniques to build more powerful face-recognition systems will definitely interest researchers in this area. The extension of Variance Ranklets to other domains will also encourage the enthusiasts to pursue it. Ranklets transform has emerged as the new star, with lots of promises for the future. We hope that this review encourages researches to try and fulfill the promises.

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