

Signal Approximation with Fourier Transform based on Scaling Orthonormal Basis Function.

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Short Communication

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ABSTRACT

In this paper, we study the properties of the transform which approximates a signal at a given resolution. We show that the difference of a signal at different resolutions can be extracted by decomposing the signal on a wavelet orthonormal basis. In wavelet orthonormal basis is a family of functions, which is built by dilating and translating a unique function. The development of orthonormal wavelet bases has opened a new bridge between approximation theory and signal processing. It is possible to keep the simplicity while improving the performance with non-linearities in a sparse representation. The analysis results imply that proposed method has lots of efficiency over other methods.

INTRODUCTION

Adapting the signal resolution allows one to process only the relevant details for a particular task. It is introduced a multiresolution pyramid that can be used to process a low resolution first and then selectively increase the resolution when the application of signal estimation in additive noise environment, linear operators have long predominated because of their simplicity, despite their limited performance. The approximation of a function at a resolution is specified by samples on a discrete grid which provides local averages of over neighborhoods size proportional [1,2,3]. We say that the sequence is a multiresolution approximation, if the following conditions hold: All the other properties of the multiresolution approximation are easily verified. The approximation at the resolution is defined as the orthogonal projection. To compute this projection, we must find an orthonormal basis. The theorem orthogonalizes the Riesz basis and constructs an orthonormal basis of each subspace by dilating and translating a single function called a scaling function. To avoid the resolution and the scale, the notation of resolution is dropped, called an approximation at provide a discrete approximation of for the case of Shannon approximations, we have constructed basis, which are orthonormal basis. A multiresolution approximation is entirely characterized by the scaling function that generates an orthonormal basis of each subspace. The properties of which guarantee that the spaces satisfy all the conditions of a multiresolution approximation. It is proven that any scaling function can be specified by a discrete filter called a conjugate mirror filter. The multiresolution causality property imposes. In particular, a basis decompose relates a dilation of the scaling function to its integer translations. The sequence can be interpreted as a discrete filter. The Fourier transformation of both sides yields and gives necessary and sufficient conditions on to guarantee this infinite product is the Fourier transform of a scaling function. The Fourier transform of the case of Shannon multiresolution approximation. We thus derive from that in the multiscale analysis, we interested in the difference between consecutive resolution scales. This difference is often called a detail signal. The approximations at resolution of a signal are respectively equal to their orthogonal projection. It can also be shown that the signal details at resolution are given by an orthogonal projection of the original signal onto the orthogonal complement of represent the orthogonal complement, it denotes a direct sum. In order to obtain the detail signal of a function, we need to find an orthonormal basis of Theorem, Scaling function and the corresponding conjugate mirror filter.

METHODS AND MATERIALS

The orthogonal projection of a signal in a detailed space is obtained with a partial expansion in its wavelet basis. signal expansion in a wavelet orthonormal basis can thus be viewed as an aggregation of details at all the

scales that goes from, Many applications using wavelet decomposition desire efficient approximations of particular classes of functions by a few non-zero coefficients. This usually requires optimizing the design to produce maximum number of wavelet coefficients that close to zero. The actual number of coefficients with non-negligible values depends on the regularity, the number of vanishing moments of the analyzing wavelet and the size of its support. A wavelet has vanishing moments if The vanishing moment is crucial to measure the local regularity of a signal. If the wavelet has vanishing moments, then it can be shown that the wavelet transformation is actually a multiscale differential operator of order. This nice property relates the differentiability with its wavelet transform decay at fine scales. Hence If a wavelet has vanishing moments, then its first derivatives are zero. it follows that if a wavelet has vanishing moments, then its corresponding conjugate mirror filter and its first derivatives are zero, we can decompose a function. As mentioned before, the number of wavelet coefficients with non-negligible values depends on not only the number of vanishing moment, but also the size of its support. Suppose has a singularity point, and is inside the support of might have a large value. If it has a compact support of size N , then at scale there must be N wavelets whose support includes the singularity point. To minimize the number of coefficients with non-negligible values, we have to choose a wavelet with a small support size. Daubechies showed that the scaling function has a compact support if and only has a compact support. On the other hand, just a dilation. The equality proves that if it has a compact support.

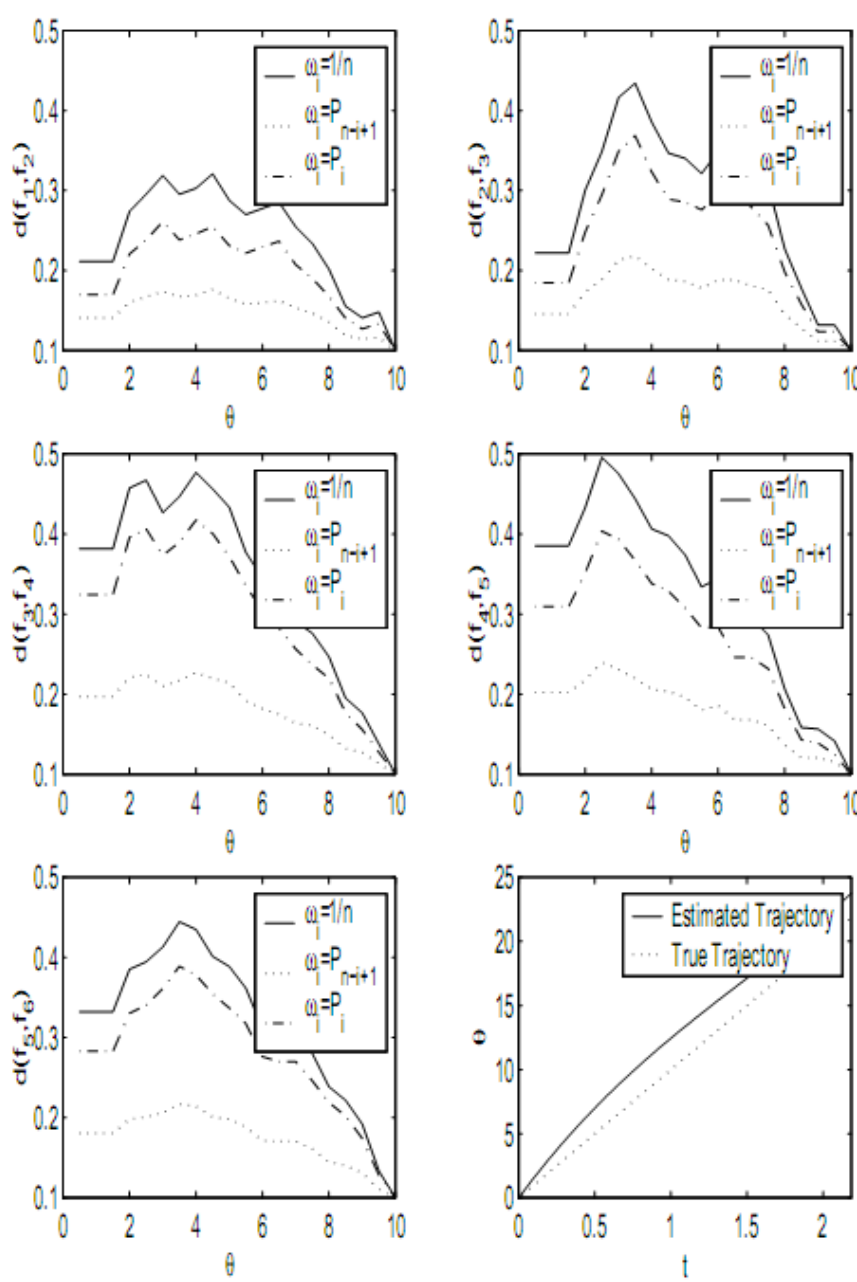


Figure 1: Signal Estimation by Fourier transforms

RESULTS AND DISCUSSION

To form a radar image, bursts of received signal are sampled and organized burst by burst into a two-dimensional array, this sample matrix is not uniformly spaced in the spatial frequency, and instead, it is polar formatted data. The Discrete Fourier Transform processing of the polar formatted data would result in blurring at the edges of the target reflectivity image. a synthetic are spatial frequency quantities defined at frequency and target rotation angle. The phase term is related to the target translational motion only, and can be compensated by traditional translational motion compensation methods. ISAR image of moving target reconstructed by the Discrete Fourier Transformation ISAR image of an aircraft target. The radar is assumed to be operating at 9GHz and transmits a stepped-frequency waveform. Each burst consists of 64 narrow-band pulses stepped in frequency from pulse to pulse by a fixed frequency step. The pulse repetition frequency is 15KHz. Basic motion compensation processing has been applied to the data. A total of 512 bursts of received signal are taken to reconstruct the image of this aircraft, which corresponds integration time. As we can see, the resulting image is defocused due to the target rotation. In fact, the defocused image in Figure 2 is formed by overlapping a series of target at different viewing angles. By replacing the Fourier transform with the time varying spectral analysis techniques, we can take a sequence of snapshots of the target during the 2 :18sof integration time. the trajectory of the target, with image frames taken respectively. Image registration can be applied to estimate the target motion from this sequence of images. For the synthetic ISAR images shown in Figure 2, we search for the rotation angles between a sequence of image frames observed in a time interval secutive target image frames. As can already be seen in the figures, uniform weights produce the sharpest peak. By interpolating, we obtain an estimated trajectory of the target rotational motion during the imaging time. An estimated trajectory of a target is particularly important since it may be subsequently used in polar re-formatting and re-sampling the received signal into rectangular format [4,5].

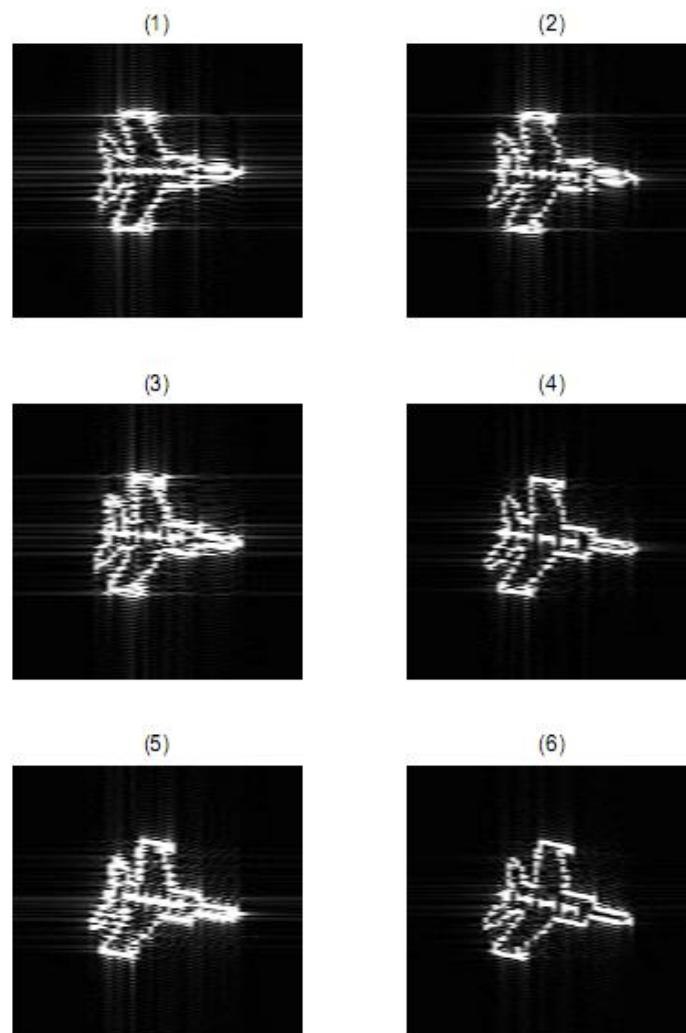


Figure 2: Trajectory of a sequence of target image frames

CONCLUSION

A new generalized divergence measure, divergence, is proposed in this paper. We prove the convexity of this divergence measure, derive its maximum value, and analyze its performance upper bounds in terms of the

Bayes error of nearest neighbor classifier. Based on the divergence, we propose a new approach to the problem of image registration. Compared to the mutual information based registration techniques, the divergence adjusts its weight and exponential order to control the measurement sensitivity of the joint histogram. This flexibility ultimately results in a better registration accuracy.

REFERENCES

1. Ajjimarangsee P, Huntsberger TL. Neural network model for fusion of visible and infrared sensor outputs. Proc SPIE. 2009;1003:153-160.
2. Sedghi T. A Fast and Effective Model for cyclic Analysis and its application in classification. Arabian J Sci Eng. 2012;38.
3. Ritter GX, Wilson JN Davidson JL. Image algebra application to multi- sensor and multi-data image manipulation. Proc SPIE. 2008;933:2-7.
4. PJ Burt, RJ Kolczynski. Enhanced image capture through fusion. Proc 10th Intl Conference on Computer Vision, pp. 173-182, 2010.
5. Van den Elsen PA, Pol E-JD, Viergever MA. Medical image matching-a review with classification. IEEE Eng Med Biol Magaz. 1993;12(1):26-39.