Comparison of 3-D Discrete Cosine and Discrete Sine Transforms for the Novelty Estimation in Volumetric Data

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Abstract— **In this paper, we discuss the use of the discrete cosine transform and discrete sine transform for the problem of novelty estimation in volumetric data. More specifically, we investigate the potential of discrete sine transform for the novelty detection. Given a system with training examples, the novelty detection is defined as the method of identifying of unknown signals which the system is not familiar with. The presented volumetric novelty estimation scheme utilizes three dimensional versions of the discrete cosine transform and discrete sine transform. We present that in the event of novelty the discrete sine transform yields higher statistical dispersion, which is a clue of the ability to expose dissimilarities, than the discrete cosine transform does.**

Keywords- novelty detection; discrete cosine transform; discrete sine transform; three dimensional data analysis; volumetric data; high dispersion

I. INTRODUCTION

Estimation of novel patterns in volumetric data is an important capability in different applications such as signal processing [1], pattern recognition [2], data mining [3], robotics [4], fault detection [5], medical imaging [6] and military defense systems [7]. The novelty detection is defined as the method of identifying of unknown signals which a system is not aware of during training process [8]. It is a well known fact that one cannot train a learning system by providing complete data from all possible categories. Instead, it is more feasible to develop a method for differentiating between known and unexpected patterns using some sort of testing. The novelty estimation is an extremely challenging task. That is why there are several existing methods that perform well on specific type of data.

In this paper, we investigate the applicability of the discrete cosine transform and discrete sine transform to the problem of novelty estimation in volumetric data. More specifically, our goal in this paper is to examine if discrete sine transform can be efficiently used for the novelty estimation. Transforms are used mainly for the reduction of complexity in mathematical computations [9]. Although the first paper about discrete cosine transform style transforms was published forty years ago [10], it is still an attractive topic for the research community. In the literature, there have been many methods using the discrete cosine transform and DST for a wide variety of methods such as image compression [11], face recognition [12], speech enhancement [13], video alignment [14], image processing [15], video coding [16], image watermarking [17], volatility measurement [18], audio decoding [19], and classification [20]. The discrete cosine transform and DST decompose a signal into specific frequency components. The definitions of different types of discrete cosine transform and discrete sine transform have been reviewed in [21]. The discrete cosine transform and discrete sine transform are real valued operations that transform discrete signal to real valued coefficients, without generating any complex numbers. This is one of the advantages over Fourier transform [22]. Moreover, the existence of fast algorithms provides efficient discrete cosine transform and discrete sine transform computation. Volumetric data can be defined as a sequence of different instances that are generated by the same data source. There is a strong correlation between successive slices in a volumetric data set. This similarity may be exploited using discrete cosine transform and discrete sine transform. In this paper, we investigate the fitness of discrete sine transform and discrete cosine transform for the problem of novelty estimation in volumetric data. The proposed method is based on certain energy compaction properties of the discrete cosine transform and discrete sine transform coefficient matrices. Many studies pointed out that the discrete cosine transform fits well for data compression and feature extraction. On the other hand, investigation of forms of discrete sine transforms has not been widely investigated. Therefore there is a need to develop discrete sine transform based techniques. In our experiments, we use the volumetric data set (i.e., set of images) provided by changedetection.net [23].

The main contribution of this paper is that we present that the discrete sign transform can be employed for the novelty detection in three dimensional data.

II. METHODS AND FEATURE EXTRACTION

Most of the earlier work on novelty detection deals with the problems about the control systems. One common approach is to model normal data and to use a threshold for detecting abnormality. Statistical approaches employ the model and its statistical properties and use this information to estimate the samples which are not generated by the same distribution. Antoniadou et al. [24] propose a set of features and use a framework to rank features for novelty detection. Foggia et al. [25] tackles the novelty estimation by combining multiple experts with the goal of compensating the weakness of each single expert. Wei et al. [26] follow a different approach and suggest injecting anomalies into the training data to help the learner determine a boundary around the original data. Tax and Duin [27] describe a set of methods for rejecting outliers based on the data density distribution.

In this paper our main goal is to compare energy compaction features of discrete cosine transform and discrete sine transform for novelty detection in volumetric data. We need a method that can exploit the characteristics of three dimensional discrete cosine transform and discrete sine transform. Therefore, we follow a similar approach proposed by Haberdar and Shah [28], where the authors develop a generic framework that can be applied to different novelty detection applications dealing with multidimensional data. They [28] extract spatiotemporal signatures of unit cube elements using a subset of discrete cosine transform coefficients and design a system for detection novelties in the case of very strong background noise. In our system, we employ their framework for the comparison of three dimensional discrete cosine transform and discrete sine transform features.

We first split the volumetric training and test data into 8x8x8 regions and compute discrete cosine transform and discrete sine transform coefficients. When the coefficient values start not fitting to the underlying training data, we conclude that there is a novelty in the data.

A. Discrete Cosine Transform

The idea behind discrete cosine transform is to try to de-correlate the input data. Most of the recent applications using discrete cosine transform employ discrete cosine transform type-two although other forms of the discrete cosine transform have been investigated in detail in the literature [29]. The discrete cosine transform type-two is probably the most commonly used form, and it is usually simply named as the discrete cosine transform. The definition one dimensional discrete cosine transform kernel used in this paper is defined as follows:

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right], \quad k = 0,\ldots,N-1, \tag{1}$$

where N is the number of elements in the input signal, k is the parameter that changes the base cosine vector, and X_k is the real valued discrete cosine transform coefficient.

The discrete cosine transform is a separable transform [30]. The advantage of being a separable transform is that a higher version of the transform can be expressed in terms of its corresponding one dimensional counterpart. In other words, we can compute two dimensional discrete cosine transform coefficients by applying one dimensional discrete cosine transform in rows and columns of the two dimensional data, respectively. Similarly, one can compute three dimensional discrete cosine transform coefficients by stacking two dimensional coefficient matrices and applying one dimensional transform for each vector in the third dimension.

B. Discrete Sine Transform

Discrete sine transform is known to be unsuitable for data compression mainly because it does not have the required uniform vector in its basis space. This aspect of it yields a poor energy compaction for highly correlated input data. Discrete sine transform also does not have a direct current (DC) coefficient. This is disadvantage for a data compression problem. On the other hand, discrete sine transform works well with de-correlated data. We can use this feature of discrete sine transform for the novelty detection because the novelty in the multidimensional data stems from the de-correlation among the neighboring data elements in all directions. The definition of discrete sine transform kernel used in this paper is defined as follows:

$$X_k = \frac{2}{N+1}\sum_{n=1}^{N} x_n \sin\left[\pi \frac{kn}{N+1}\right], \quad k = 1,\ldots,N., \tag{2}$$

where N is the number of elements in the input signal, k is the parameter that changes the base sine vector, and X_k is the real valued discrete sine transform coefficient. Discrete sine transform is also a separable transform. For both discrete cosine transform and discrete sine transform, the inverse transforms can reconstruct the input data perfectly because they are both lossless transforms. On the other hand, in our investigation we do not use the inverse transformation of discrete cosine transform and discrete sine transform. The interested reader is encouraged to read the paper of Zheng et al. [31].

C. Novelty Estimation Algorithm

The novelty estimation algorithm is a two step process. The first step is a non-parametric classification method similar to a k-nearest neighborhood [32]. Instead of building a classification model and estimating the parameters of the model, the instances of the training data are used to approximate a local decision function. The drawback of this method is that it is sensitive to the local structure of the data. On the other hand, it has a low computational complexity, which is quite important for the case of massive three dimensional data. We first compute the discrete cosine transform and discrete sine transform coefficient matrices of the baseline data, where the slices in the data has only minor changes that mimic the natural noise in the environment. The baseline data constitutes our training set, and we store these values in our system. Then, when the system examines a test data item, we compute the discrete cosine transform and discrete sine transform coefficients of the test volumes. Finally, we compare a test volume to the spatially related volumes in the training set. When there is a significant deviation in the mean absolute values between training and test examples, we label it as a sign of the novelty.

At this point, we should emphasize that our goal in this paper is neither to design a complete novelty estimation framework nor define a threshold for the decision. Instead, we focus on the comparison of the discrete cosine transform and discrete sine transform outputs. We would like to emphasize the observation that discrete sine transform may fit well for the problem of novelty detection. Accordingly, we compare and contrast the distribution of discrete cosine transform and discrete sine transform outputs when there is an anomaly in the volumetric data. We try to determine how and in what degree the discrete sine transform reflects the anomalies better than discrete cosine transform.

III. Results and Discussions

The main test scenario followed in the experiments is as follows. We are given a set of slices of any type of volumetric data taken by some static data acquisition sensor. These sequential slices constitute the volumetric test and training data. We should also make it clear that we did not use our test data in the training data. Our goal is to identify the data blocks within a volume that expose different characteristics from the previous blocks.

We use a measure of dispersion, which expresses quantitatively the degree of variation or dispersion of values in a population, to compare discrete cosine transform and discrete sine transform outputs. Some of measures of dispersion are the standard deviation, the range, and the average deviation. We compute the standard deviations of each output (Fig. 1) and analyze it to compare them.

A. Experiments with Synthetic VomuetricData

In the first set of the experiments, we generate synthetic volumetric data and add Gaussian noise to the data. The real data do not always have the ground truth. Furthermore, specific needs or certain conditions that may not be found in the real data can be tested in this way. The noise parameters of the baseline volumetric data are mean and standard deviation:

$$\mu=10 \text{ and } \sigma=5. \tag{3}$$

We add noise to the data in order to simulate the real world conditions. It is a well known fact that the data acquisition sensors and the environment where the experiment takes place always generate different kinds of noise.

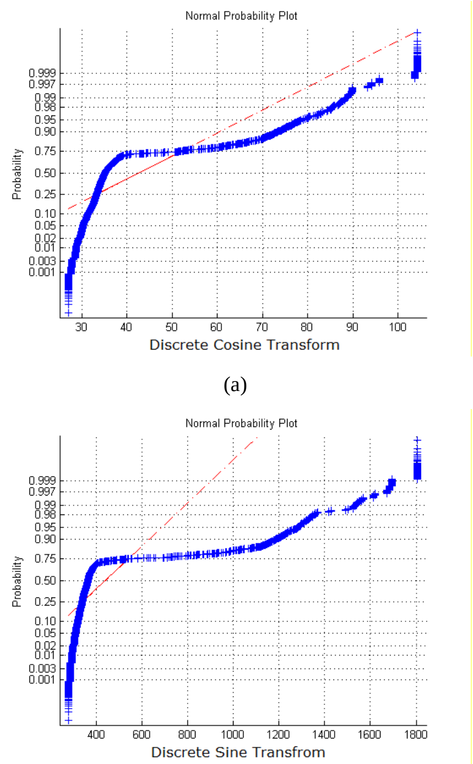


Figure 1. When there is no novelty in the data, one can assume that the distribution of estimation values will come from a normal distribution. In this figure, we graphically present how much the compare discrete cosine transform and discrete sine transform outputs deviate from the normal distribution. When there is no novelty in the volumetric data, we expect a linear plot. Curvatures in the plots are the hints of detecting novelty in the volumetric data. This specific example is produced from the output of the library data set [23].

After generating the test and training data, we generate test data with time varying artificial changes. The second set of the data is labeled as the test data. After generating the artifacts in the data, Gaussian noise is also added. These steps help us to observe how the robust the proposed framework is. In Fig. 2, we present sample training slices.

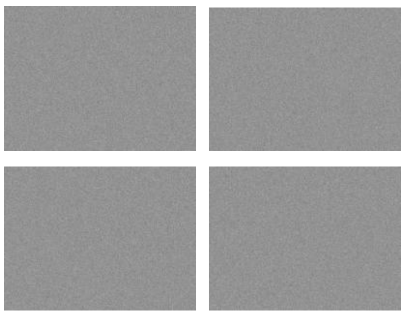


Figure 2. Slices of the baseline volume data with the Gaussian noise.

For the test slices, we add square shaped artifacts in order to simulate novelty in three dimension. Examples of the test slices are presented in Fig. 3.

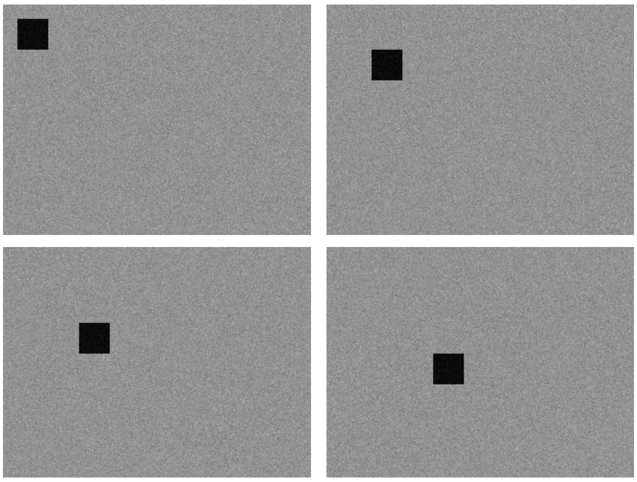
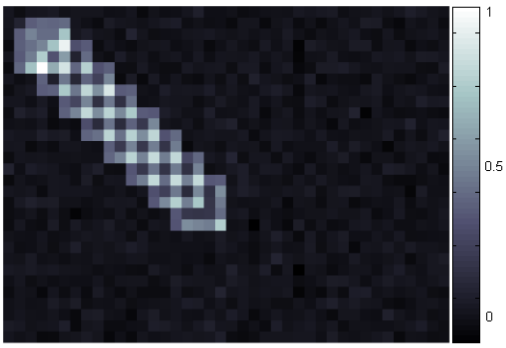
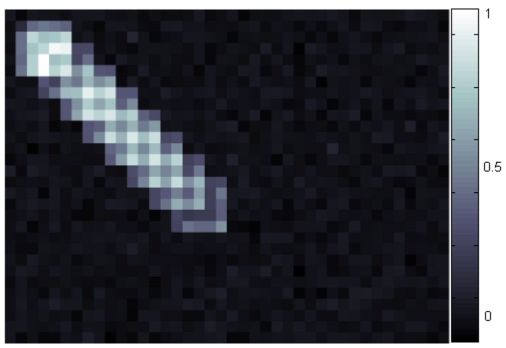


Figure 3. Some of the slices of the artificial volumetric change in the synthetic data. We add Gaussin noise into the test data as well.

We group the slices of volumetric test data in such a way that we can apply three dimensional transform to 8x8x8 voxels. the are an exception to the prescribed specifications of this template. We present the summary of the novelty in the volume using a two dimensional image in Fig.4 .



(a) Discerete cosine transform output



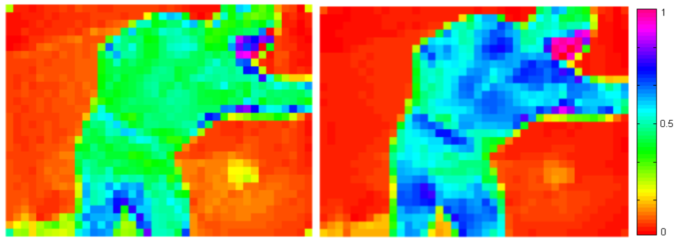
(b) Discrete sine transform ouput

Figure 4. Results of the experiment using synthetic volumetric data. A value above 0.5 may be considered as the existence of a volumetric novelty.

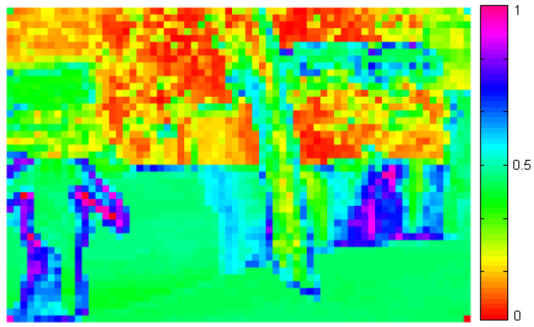
In the case of synthetic volumetric data, we observe that DST yields outputs where the artifact can be determined more clearly. Moreover, the DST can cope with noise efficiently.

B. *Experiments with Real VomuetricData*

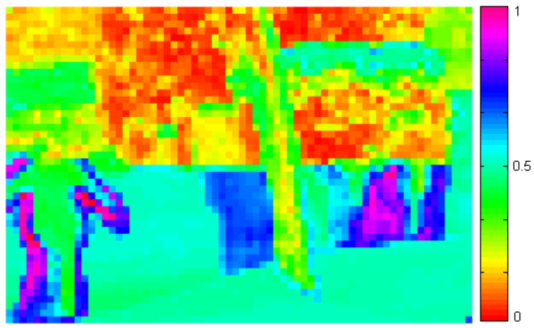
In the second set of experiments, we use real volumetric data which are obtained from changedetection.net [23] data benchmark. There are several categories in the data set. To perform objective comparisons between the discrete sine transform and discrete cosine transform, volumetric data from different categories of changedetection.net video dataset [23] are employed.



(a) (b)



(c)



(d)

Figure 5. We present novelty detection results using the discrete cosine transform and discrete sine transform for the real data. A value above 0.5 may be considered as the existence of a volumetric novelty. In (a) and (b) we present examples for the library data set, and in (c) and (d) we present examples for the skating data set [23]. In (a) and (b), we present the novelty detection results for discrete cosine and discrete sine transforms, respectively. When there is a volumetric change, discrete sine transform yields output that has much higher standard deviation than discrete cosine transform does. This shows that discrete sine transformgenerates a larger margin between regions of novelty and static regions. These results show that discrete sine transform almost always yields more diverse values such that it would be easier to

estimate the novelties. Similaryly, in (c) and (d), we present the novelty detection results for discrete cosine and discrete sine transforms, respectively.

The real data obtained from [23] consist of sets of images where there is no significant change in the data. At the same time, for some of the sets of images there are different types of changes. In Fig. 5, we present the result of the library data set and the skating data set. We observe that novelty detection using discrete sine transform determines the changes much better. The range between the un-changed voxels and changed vixels are larger for discrete sine transform. When there is a volumetric change, discrete sine transform yields output that has much higher standard deviation than discrete cosine transform does. This shows that discrete sine transform generates a larger margin between regions of novelty and static regions. In Fig. 6, we show another set of results.

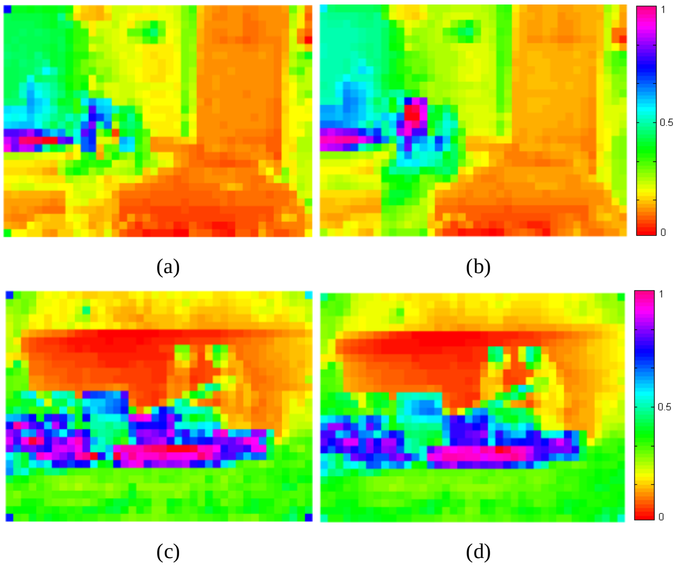


Figure 6. A value above 0.5 may be considered as the existence of a volumetric novelty. In (a) and (b), examples of office data set and in (c) and (d) examples of lakeside data set are presented [23]. (a) and (c) are the discrete cosine transform results. (b) and (d) are discrete sine transform results. These results show that discrete sine transform specifies the novelty better than discrete cosine transform does. On the other, in the images (c) and (d), the difference between the images is not as clear as the other examples. This is the worst result we observe.

IV. Conclusions

In this paper we have presented a comparative study of novelty detection for volumetric data using the discrete cosine transform and discrete sine transform. Based on our preliminary results, we are encouraged to continue our investigation of using discrete sine transform for the novelty detection in volumetric data. We observe that for volumetric data with high correlation, the discrete cosine transform yields better results; however, for the data with a low correlation of coefficients–which corresponds to case of the novelty in the data, the discrete sine transform yields better energy compaction. Given the fact that the novelty stems from the de-correlation in the data, discrete sine transform is a very good candidate for this purpose. We plan to perform more tests using computer tomography scans by dividing the slices into regions of interest. The potential of discrete sine transform for the anomaly detection in medical image data would be our future work.

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References

[1] J.P. Bello, L. Daudet, S. Abdallah, C. Duxbury, M. Davies, M.B. Sandler, B. Mark, “A tutorial on onset detection in music signals,” Speech and Audio Processing, IEEE Transactions on , vol.13, no.5, pp.1035,1047, Sept. 2005.

[2] X. Li, and W. B. Croft, “Novelty detection based on sentence level patterns,” In Proceedings of the 14th ACM international conference on Information and knowledge management, pp. 744-751, ACM, 2005.

[3] U. Fayyad, G. Piatetsky-Shapiro, and P. Smyth, “From data mining to knowledge discovery in databases,” AI magazine, 17(3), 37, 1996.

[4] S. Marsland, U. Nehmzow, and J. Shapiro, “On-line novelty detection for autonomous mobile robots,” Robotics and Autonomous Systems, 51(2), pp. 191-206, 2005.

[5] D. Dasgupta, and F. Nino, “A comparison of negative and positive selection algorithms in novel pattern detection,” Systems, Man, and Cybernetics, IEEE International Conference on , vol.1, pp.125-130, 2000.

[6] L. Tarassenko, P. Hayton, N. Cerneaz, and M. Brady, “Novelty detection for the identification of masses in mammograms,” Artificial Neural Networks, Fourth International Conference on, pp. 442-447, 1995.

[7] G.A. Carpenter, M.A. Rubin, and W.W. Streilein, “Familiarity discrimination applied to radar target recognition,” Proceedings of the International Conference on Neural Networks, Vol. 3, pp. 1459 –1464, 1997.

[8] M. Markou, S. Singh, “Novelty detection: a review—part 1: statistical approaches”, Signal Processing, vol. 83 (12), pp. 2481-2497, 2003.

[9] V. Britanak, P.C. Yip and K.R. Rao, Discrete cosine and sine transforms: general properties, fast algorithms and integer approximations. Academic Press, San Diego, CA, 2010.

[10] N. Ahmed, T. Natarajan, and K.R. Rao, “Discrete Cosine Transform,” Computers, IEEE Transactions on , vol.C-23, no.1, pp.90,93, 1974.

[11] Y. Yang, N.P. Galatsanos, and A.K. Katsaggelos, “Regularized reconstruction to reduce blocking artifacts of block discrete cosine transform compressed images.” Circuits and Systems for Video Technology, IEEE Transactions on, 3(6), pp. 421-432, 1993.

[12] Z.M. Hafed and M.D. Levine. “Face recognition using the discrete cosine transform,” International Journal of Computer Vision, 43(3), 167-188, 2001.

[13] I.Y. Soon, S.N. Koh, and C.K. Yeo, “Noisy speech enhancement using discrete cosine transform,” Speech communication, 24(3), pp. 249-257, 1998.

[14] H. Haberdar and S.K. Shah, “Video synchronization as one-class learning,” In Proceedings of the 27th Conference on Image and Vision Computing New Zealand, pp. 469-474, ACM 2012.

[15] S.A. Martucci, “Image resizing in the discrete cosine transform domain,” In Image Processing Proceedings, International Conference on, vol. 2, pp. 244-247, IEEE, 1995.

[16] J. Han, A. Saxena, and K. Rose, “Towards jointly optimal spatial prediction and adaptive transform in video/image coding,” In Acoustics

Speech and Signal Processing (ICASSP), International Conference on pp. 726-729, IEEE, 2010.

[17] S. Goyal and R. Sharma, "The medical image watermarking algorithm with encryption by discrete sine transform," International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3(6), pp. 390-395, 2013.

[18] G. Curci and F. Corsi, "Discrete sine transform for multi-scale realized volatility measures," Quantitative Finance, 12(2), pp. 263-279, 2012.

[19] V. Britanak, "New generalized conversion method of the MDCT to MDST coefficients in the frequency domain for arbitrary symmetric windowing function," Digital Signal Processing, vol. 23 (5), pp. 1783–1797, 2013.

[20] H.B. Kekre, T.K. Sarode, and J.K.Save, "Image classification in transform domain," International Journal of Computer Science and Information Security (IJCSIS), 10(3), 91-97, 2012.

[21] K. Rose, A. Heiman, and I. Dinstein, "DCT/DST alternate-transform image coding," Communications, IEEE Transactions on , vol.38, no.1, pp. 94–101, 1990.

[22] I.Y. Soon, S.N. Koh, "Speech Enhancement Using Two Dimensional Fourier Transform", IEEE Trans. Speech and Audio Processing, vol 11, No. 6, Nov 2003, pp 717-724.

[23] N. Goyette, P. Jodoin, F. Porikli, J. Konrad, and P. Ishwar, "Changedetection.net: a new change detection benchmark dataset," Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition (Sherbrooke, Canada, 2012), pp. 1–8.

[24] I. Antoniadou, N. Dervilis, R.J. Barthorpe, G. Manson, K. Worden, "Advanced tools for damage detection in wind turbines," Key Engineering Materials, pp. 547-554, 2013.

[25] P. Foggia, C. Sansone, F. Tortorella, and M. Vento, "Multiclassication: reject criteria for the bayesian combiner," Pattern Recognition 32 pp. 1435–1447, 1999.

[26] F. Wei, M. Miller, S.J. Stolfo, L. Wenke, P.K. Chan, "Using articial anomalies to detect unknown and known network intrusions," Proceedings of the IEEE International Conference on Data Mining, ICDM, pp. 123–130, 2001.

[27] D.M.J. Tax and R.P.W. Duin, "Data description in subspaces," International Conference on Pattern Recognition, Vol. 2, 2000.

[28] H. Haberdar and S.K. Shah, "Change detection in dynamic scenes using local adaptive transform," Proceedings of the British Machine Vision Conference, BMVA Press, pp. 6.1–6.12, 2013.

[29] S.A. Martucci, "Symmetric convolution and the discrete sine and cosine transforms," Signal Processing, IEEE Transactions on, 42(5), 1038-1051, 1994.

[30] S.A. Khayam, "The discrete cosine transform (dct): theory and application," Michigan State University, 2003.

[31] Z. Zheng, Z. Jiang, and F. Sijstermans, "Unified inverse discrete cosine transform (IDCT) microcode processor engine," U.S. Patent No. 8,126,952. 28, 2012.

[32] J.M. Keller, M.R. Gray, and J.A. Givens, "A fuzzy k-nearest neighbor algorithm," Systems, Man and Cybernetics, IEEE Transactions on, (4), pp. 580-585, 1985