Innovative Keratoconus Health Monitoring System using Thermal Images through Fractional Spline Wavelet Transform and compared with Discrete Wavelet Transform

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Abstract : The aim of this study is to monitor the Keratoconus with thermal image using Fractional Spline Wavelet Transform (FSWT) and comparing the Structural Similarity index (SSIM) with Discrete Wavelet Transform (DWT). Materials and methods: Thermal image of an eye is captured using a thermal camera for 9 samples and it is applied to FSWT, sub bands are obtained from transformed image and SSIM is extracted using resynthesized image. Group 1 is considered as FSWT and group 2 is using DWT, each consisting of 9 samples. There are 18 samples in all, with a pretest G power of 80%. Results: In this study, FSWT has a higher average SSIM of 195.2 than DWT, which has an average SSIM of 170.5, and the significance is $p<0.05$. Conclusion: Within the confines of our research, it is observed that innovative keratoconus health assessment using thermal images through FSWT has higher significance than DWT.

IndexTerms **-** Innovative Keratoconus health assessment, Fractional Spline Wavelet Transform, feature extraction, Structural Similarity Index, Discrete Wavelet Transform, Thermal image.

I. Introduction

Keratoconus is a disorder that affects the structure of the cornea and results in visual loss. It is the condition in which clear tissue on the front of the eye - cornea bulges outwards into a conical shape (Pinos-Velez et al. 2017). The Central thinning, conical shape, and corneal expansion are signs of keratoconus. The author proposed a deep learning network called KerNet to detect Keratoconus. The raw data from the Pentacam HR system is used in this way, which has a 92.91 percent accuracy and comprises 5 slices for each sample (Feng et al. 2021). Keratoconus disease varies by geographical location ranging from 0.0002 percent to 2.34 percent. It is necessary to diagnose people in order to provide them with good and healthy eyesight and so improve their quality of life. The author uses Convolutional Neural Network to detect keratoconus and obtained an accuracy of 97.5% with 126 learning cycles (Lavric et al. 2019). At an early stage of illness, the cornea is thinner and appears normal on the outside, the parameter Keratoconus index is used to detect the progression of keratoconus in the eyes. Ultrasound image is captured from ultrasound bio microscopy to evaluate keratoconus index and it is found to be 0.975074 (Castiglione and Castiglione 2000). Early detection of Keratoconus can prevent vision loss and can reduce the treatment costs.

There are many researchers working on Keratoconus, 75 papers published in IEEE, 14,600 articles in google scholar and 8650 papers in ScienceDirect. Smart phones are being used to assist the ophthalmologist to detect eye disease by magnifying the eye images. The author used a Support Vector Machine (SVM) with an accuracy of 89 percent to differentiate keratoconus eyes from healthy eyes. Gradient slope detection, which uses a 90-degree view of the eye, is used to detect different stages of keratoconus, and the Prewitt operator is utilized to recognize edges (Askarian et al. 2019). A deep learning-based unsupervised and semi-supervised classification algorithm is presented to diagnose keratoconus at an early stage, with the goal of providing earlier treatment. Using 124 tests, they reached an accuracy level of 80.3%. The number of samples is not sufficient to detect keratoconus of the eyes and their findings are not generalized (Hallett et al. 2020). The author applied a SVM algorithm to detect placido ring edges. By placido of a scheimpflug camera, features are extracted and tested 1059 normal eyes, 677 keratoconus eyes and 226 subclinical images and obtained an accuracy of 96.9% (Arbelaez et al. 2012). The algorithm used in detecting keratoconus involves many parameters which results in complexity of implementation and testing. Corneal topography, corneal aberration are the methods used to detect irregular levels of keratoconus and normal eye is compared with keratoconus eye (R, Kanimozhi, and Gayathri 2020).

Diagnosis and management of Keratoconus has not been analyzed till now and Keratoconus detection was done using various algorithms. These algorithms are more complex and involve many parameters. Keratoconus was not detected by measuring SSIM previously. Earlier, Kerato Index (KI) was used as a parameter to diagnose keratoconus. In this study, Keratoconus is detected through FSWT by calculating SSIM values. The existing algorithms are having low efficiency. The aim of this research is to detect innovative Keratoconus health assessment using thermal images through FSWT and comparing with DWT.

II. Materials And Methods

This study is being conducted in the Digital Signal Processing laboratory of the Department of Electronics and Communication Engineering at Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai. The proposed work consists of two groups. Each group has 9 samples, with group 1 being FSWT and group 2 being DWT, with a sample size of 18. The sample size is calculated as 18 with pretest G power of 80% and significance value is < 0.05 using clincalc.com (Verma and Verma 2017).

In group 1, the samples of thermal images are given to FSWT . The original image of an eye is captured through a thermal camera and thermal image is obtained and undergoes feature extraction through FSWT and Spline filters are evolved and image is resynthesized and it is shown in fig. 5.

In group 2, the samples of thermal images are given to DWT. Here the original image of an eye is converted to a thermal image using a thermal camera and feature extraction is done through DWT and synthesized image is obtained.

Simulation block diagram of Keratoconus health monitoring system using thermal images through FSWT is shown in Fig. 1. Thermal imaging is the process of converting infrared radiation into electrical signals and image is created by using infrared radiation emitted from objects. In this paper, thermal images of eyes for 9 subjects are taken to detect keratoconus through FSWT. First, the thermal image is transformed to a grayscale image, and then the image is read, scaled, and applied to FSWT Filters in MATLAB. There are 3 types of spline filters - ortho, B-spline and dual spline and here ortho type is used. The parameters of FSWT used are alpha and tau where alpha = 1.5, tau = 0.3. In FSWT, analysis and synthesis are done and sub band HH is obtained at depth 2. Then it undergoes feature extraction, resynthesis error and SSIM are obtained. SSIM value can be found from the synthesized images of FSWT and DWT respectively.

The experiment set-up is done in Windows platform configuration of intel i5, 10^{th} gen, 64-bit processor, 8 GigaBytes RAM, Asus Vivo Book laptop and MATLAB 2021a software.

Fractional Spline Wavelet Transform

The author Blu represented practical FSWT which is based on fractional B-splines (Blu and Unser, n.d.). It interpolates between B-splines polynomials with integer degrees, allowing fractional order approximation. ST performs the function of fractional differentiators. By adjusting the degree of spline wave transform, the noise $1/f^{\alpha}$ noise can be removed. Scaling functions are used to define ST.

The one-sided fractional B-splines is given by

$$\beta_*^{2n}(x) def \frac{\Delta_+^{\alpha+1} x_+^{\alpha}}{\Gamma(\alpha+1)} = \sum_{k\geq 0} \frac{(-1)^k \binom{\alpha+1}{k}}{\Gamma(\alpha+1)} (x-k)_+^{\alpha} \quad (1)$$

Where α > -1/2.

If α is not even,

$$\beta_*^{2n}(x) =^{def} - \frac{\Delta_*^{2n} x_*^{\alpha}}{2 sin\left(\frac{\pi}{2}\alpha\right) \Gamma(\alpha+1)}$$

$$= \sum_{k\in z} \frac{(-1)^{k+1} \left|\begin{matrix}\alpha+1\\ k\end{matrix}\right|}{2sin\left(\frac{\pi}{2}\alpha\right)\Gamma(\alpha+1)} |x-k|^{\infty} \quad (2)$$

If α is even,

$$\beta_*^{2n}(x) =^{def} \frac{(-1)^{n+1}}{\pi\Gamma(2n+1)} \Delta_*^{2n+1} x_*^{2n}$$

$$= \frac{(-1)^n}{2n!\pi} \sum_{k\in z} (-1)^{k+1} \left|\begin{matrix}2n+1\\ k\end{matrix}\right| |x-k|^{2n} log|x-k| \quad (3)$$

The orthonormalized fractional B-splines is given by

$$H_{\perp}^{\alpha}(e^{j\omega}) = H^{\alpha} e^{-j\omega} \sqrt{\frac{A^{2\alpha}+1(e^{j\omega})}{A^{2\alpha+1}(e^{2j\omega})}} \quad (4)$$

Where $A^{\alpha}(z)$ represents an autocorrelation filter for a B-spline of degree α given by

$$A^{\alpha}(e^{j\omega}) = \sum_{n\in z} e^{-jn\omega} \int \beta_+^{\alpha}(x)\beta_+^{\alpha}(x+n)dx \quad (5)$$

By combining the scaling functions linearly, the wavelets are constructed. The generating filter's frequency response is given by

$$G_{\perp}^{\alpha}(e^{j\omega}) = e^{-j\omega} H_{\perp}^{\alpha}(e^{-j\omega}) \quad (6)$$

using wavelet theory.

Statistical analysis

Simulation has been carried out in MATLAB. The SSIM comparison of FSWT with DWT is done in IBM SPSS version 2.1 (McCormick and Salcedo 2017). Because the variables are unrelated, the SSIM of FSWT and DWT are compared using an independent sample T-Test, allowing for a new keratoconus health evaluation.

III. RESULTS

The original image of a human eye is captured through a thermal camera and it is converted into a thermal image which is converted to a grayscale image. Then it is applied to FSWT for feature extraction of the sub band wavelets. In this research work of detecting Innovative Keratoconus health assessment, both the techniques appear to produce the different variable results with SSIM. Table 1 shows the SSIM values calculated for FSWT and DWT techniques. For FSWT and DWT, Table-2 provides the number of samples, mean, standard deviation, and standard error mean of SSIM. Table 3 demonstrates the mean, standard deviation, and significant variance between the FSWT and DWT procedures using an Independent T-test with a p-value less than 0.05.

The Gray scale picture of the original image is shown in Fig. 2. Fig. 3 shows the Sub band HH at depth 2 from FSWT. Sub band levels of FSWT with ortho type alpha=1.5,tau=0.3 for thermal image captured from the eye is shown in fig. 4 . Resynthesized image from sub band LL at depth 3 for FSWT with alpha=1.5,tau=0.3 is shown in fig. 5. Scaling function and wavelet function of an ortho type spline filter is shown in fig. 6. Statistical analysis of Keratoconus health monitoring system using thermal images through thermal image and comparison of FSWT and DWT techniques in terms of SSIM is shown in fig. 7.

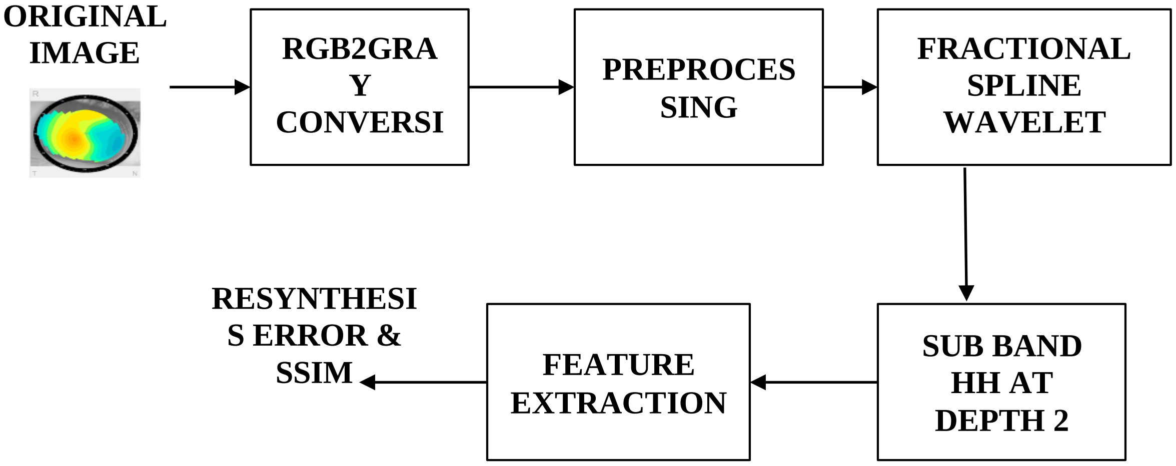

Fig. 1 Simulation block diagram of Innovative Keratoconus health monitoring system using thermal images through Fractional Spline Wavelet Transform.

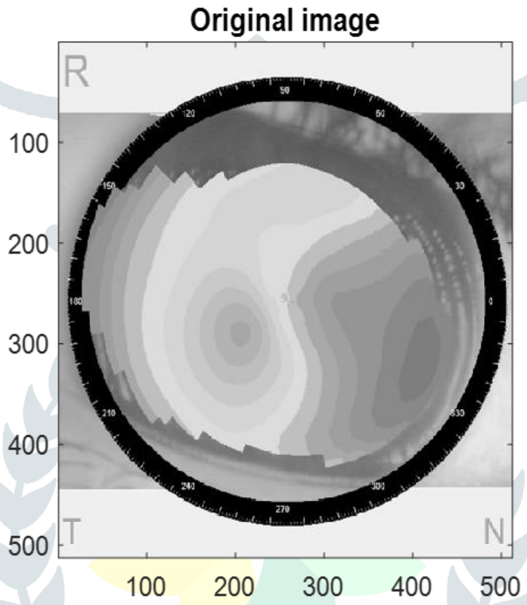

Fig. 2 Grayscale image of original image for eye captured using thermal camera.

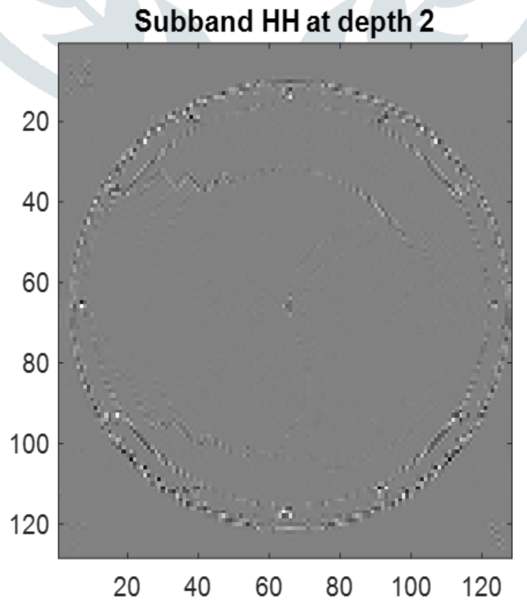

Fig .3 Subband HH at depth 2 obtained from FSWT applied to thermal image captured for eye.

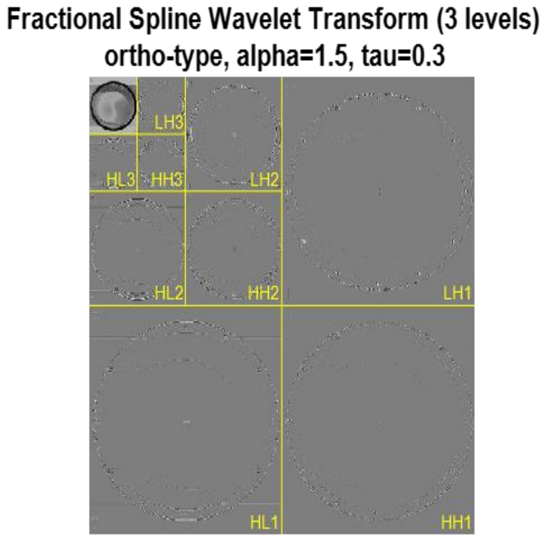

Fig .4 Subband levels of FSWT with ortho type, alpha=1.5, tau=0.3 for thermal image captured from eye

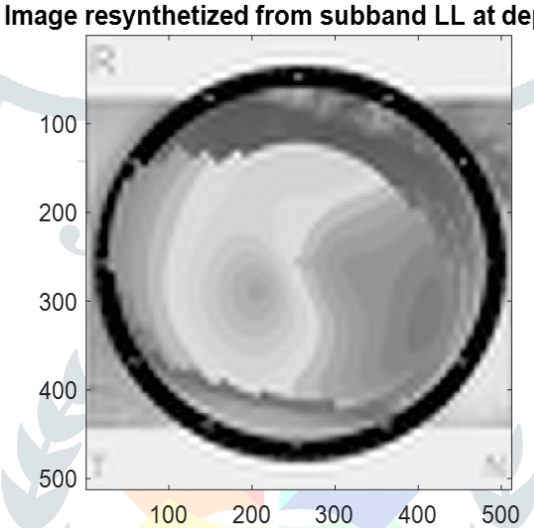

Fig .5 Resynthesized image from subband LL at depth 3 for FSWT with alpha=1.5,tau=0.3

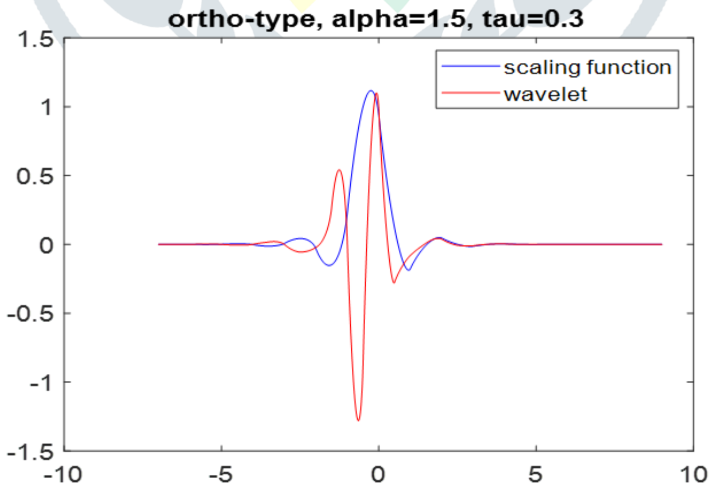

Fig .6 Scaling function and Wavelet function for an ortho type spline filter with alpha=1.5, tau=0.3

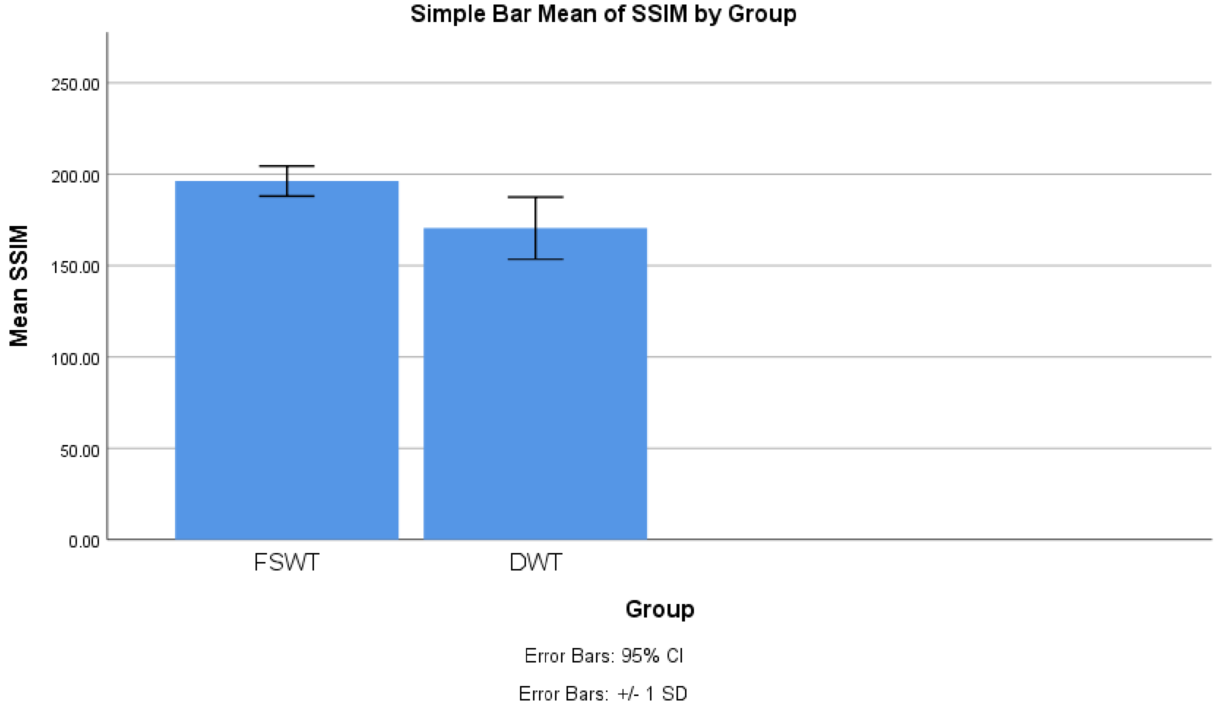

Fig. 7 Statistical analysis of Keratoconus health monitoring system using thermal images through thermal image.Comparison of FSWT and DWT techniques in terms of SSIM. FSWT has a slightly better mean SSIM than DWT and a slightly better standard deviation than DWT. X Axis: FSWTvs DWT Y Axis: Mean SSIM of detection ± 1 SD.

Table 1. Structural Similarity Index(SSIM) values for Fractional Spline Wavelet Transform(FSWT) and Discrete Wavelet Transform(DWT)

S.NO	Fractional Spline Wavelet Transform(FSWT)	Discrete Wavelet Transform(DWT)
1	215	200
2	201	189
3	195	183
4	190	171
5	199	167
6	196	162
7	191	161
8	193	153
9	187	149

Table 2. Group Statistics Results-FSWT has a mean SSIM of 196.3333 and std.deviation of 8.26136 whereas DWT has mean SSIM of 170.5556 and std.deviation of 17.00082.

Group Statistics					
	Group	N	Mean	Std.Deviation	Std.Error Mean
SSIM	FSWT	9	196.3333	8.26136	2.75379
	DWT	9	170.5556	17.00082	5.66694

Table 3. Independent T-test showing the mean, standard deviation and significant difference between FSWT and DWT methods that is less than 0.05(i.e.0.046)

		Independent Samples Test								
		Levene's Test for Equality of Variances					T-test for Equality of Means			
	Accuracy	F	Sig	t	df	Sig(2-tailed)	Mean Difference	Std.Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Values	Equal variances assumed	4.695	0.046	4.091	16	0.001	25.77778	6.30060	12.42111	39.13445
	Equal variances not assumed			4.091	11.579	0.002	25.77778	6.30060	11.99434	39.56121

IV. Discussion

According to the results of the statistical analysis, FSWT outperforms DWT in detecting innovative keratoconus health assessments. By using MATLAB software, thermal images undergo feature extraction to produce synthesized images and the SPSS result shows that the significant value is found to be 0.045. The proposed FSWT exhibits good curves in results and produces higher SSIM values compared to DWT.

Image fusion is a process of combining a certain number of images to produce a new image. The Gibbs phenomenon gives rise to the Shearlet transform, which generates large-scale image data. The Fractional Wavelet Transform can merge distinct gray distribution feature images while avoiding a lot of data transmission and fusion time (Ji and Zhao 2016)**.** To analyze the performance of the SVM algorithm, the author used multi-layer perceptron and radial basis function neural network classifiers. These classifiers are dependent on orbscan 2 data and helpful for Keratoconus detection and attributed a significance of $p < 0.05$ (Souza et al. 2010). The author proposed that Video keratography-derived indices are more accurate than ultrasonic pachymetry readings in distinguishing keratoconus from the general population. This could be due to the wide range of corneal thickness in the general population, or it could be due to ultrasonic pachymetry's failure to detect corneal thinning in keratoconus by measuring standard spots on the cornea. Because the false-negative and false-positive rates are much higher than those obtained by video keratography, pachymetry should not be used to rule out or diagnose keratoconus. In both normal and keratoconic eyes, the range of corneal thickness overlapped significantly. Video keratography indices had a 97.5 percent correct classification rate in discriminant analysis, while pachymetry data had an 86.0 percent rate with a P of 0.01 significance (Rabinowitz et al. 1998). The author used a procedure to assess the association between keratoconus (KC) and common allergic conditions like asthma, atopic dermatitis, and allergic rhinitis in a large-scale database, as well as conduct a cross-sectional study to estimate the epidemiologic relationship between KC and allergic diseases in a cross-sectional study. There was a strong link between asthma and allergic rhinitis, but no link between other allergy disorders and KC, according to the findings. An increased risk of KC is unmistakably connected to the severity of an allergic reaction (Merdler et al. 2015).

Although various methods and techniques are used for the detection of Keratoconus, there is no particular method or procedure to diagnose keratoconus and find a cure for this. Future investigation may include that diagnosis can be applied to diabetic patients, aged people. The development of technology in detecting Keratoconus by using SSIM and discovering a treatment for Keratoconus to abandon the progression of this disease.

V. Conclusion

It is observed that FSWT has a higher average SSIM of 195.2 than DWT with average SSIM OF 170.5. In this study of Keratoconus health assessment using thermal images, the FSWT gives better results when compared to DWT. The performance also continuously increased with an increase in data. This model is very efficient and holds a good potential to improve Innovative Keratoconus health assessment, hence can be implemented.

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