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<sup>1</sup>Kharkiv National University of Radio Electronics, Nauky Ave. 14, Kharkiv, 61166, Ukraine**Ky Fan norm application for video segmentation**

**Annotation.** This article presents results of applying the Ky Fan norm in the context of solving the problem of video segmentation. Since the task of video analysis can be considered as analysis of the sequence of images, it was decided to find a way to formalize the description of the video frame using the mathematical apparatus of non-square matrices. When choosing a method, particular attention was paid precisely to universality with respect to the dimension of the initial data due to the technical characteristics and nature of the video data - video frames are matrices of arbitrary dimension. The ability to skip the step of matrix transformation to square dimension, or vectorization using some descriptor allows you to reduce computational costs required for this transformation. It was decided to use the value of the Ky Fan norm as an image descriptor, since it is built on top of matrix singular values. As it is known, singular values are calculated during the singular decomposition of the matrix and can be used, among other features, to reduce the dimension of the source data. A singular decomposition does not impose restrictions on either the dimension or the character of the elements of the original matrix. In addition, it can be used to derive other matrix decompositions with required characteristics. A comparative analysis of the effectiveness of the obtained descriptor was carried out in the case of using the k-norm and l-norm, which showed that the l-norm allows us to identify the most significant changes in the scene, while k-norm is able to detect minor. In other words, depending on the context of the source video data and the scope of the developed application, it is possible to configure the sensitivity of the application to a change in the scene by varying the number of singular values involved. The decision about the presence of changes in the context of video scene is made based on a comparison of descriptors of two consecutive images, that is, the values of the Ky Fan norm.

**Keywords:** Video stream segmentation; Ky Fan norm; Singular value decomposition

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**Introduction.** Video segmentation is an area of current interests in the field of video processing and computer science. It affects dealing with big data storages, streaming video analysis, processing data from surveillance cameras and so on. Recent researches show that fundamental mathematical apparatus like time series and cluster analysis can be successfully applicable to detect scene changes and key frames [1-2].

When it comes to solving video stream segmentation and identifying key frames, special attention is needed to the formation of a descriptor and the method of comparing two descriptors. This topic is wide enough and is actively developed. Newest achievements and novel mechanisms are published in [3-6]. Brief results overview received for comparison of widespread descriptors used in open source tools is described in [7].

As it is shown, the mathematical apparatus applicable to the description of video frames is extremely diverse and includes fundamental techniques like time series [8-9], neural networks [10], cluster analysis [11] and other. Choosing an approach, attention should be paid to the technical characteristics and content of the video data, as well as the purpose and scope of the developed method. For example, how sensitive the method should be to minor changes in the

scene, whether processing is performed in real time, or delayed, what are the shooting conditions, etc. As already mentioned, the analysis of video data involves dealing with images, which in turn comes down to working with matrices of a certain dimension.

For example, in [12] approach based on color co-occurrence matrices is used to describe the video frames and generate a synopsis with the most representative frames. In [13] algorithm based on the L1-norm by accumulating action frames via optical flow method shows that it outperforms the-state-of-the-art algorithms in terms of compression ratio.

Special attention should be paid to matrix decompositions, which allow us to represent the original matrix in the form that has the required characteristic (for example, symmetry, orthogonality, etc.). In machine learning, matrix decomposition is actively used to identify in the initial data hidden, at first glance, patterns and relationships (the task of personalizing content, the task of predicting user behavior based on previous actions).

Speaking about the analysis of video data, special attention should be paid to decompositions that allow to reduce the dimension of data, since this allows to reduce the requirements for the necessary computing resources. The most used matrix decompositions that allow one to reduce dimension are the principal component method, nonnegative matrix decomposition, and singular decomposition. In this

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paper, we will consider the possibility of using the singular decomposition of the matrix and Ky Fan norm as an application to processing video data.

**The purpose of the article.** The purpose of this article is to develop a method for video segmentation based on results of singular value decomposition (SVD) applied to video frames. Since Ky Fan norm is built on top of SVD, it was taken as a descriptor for individual video frame. In other words, video is represented as a sequence of images which in turn are matrices. For each matrix SVD is applied so that Ky Fan norm can be retrieved. Incorporating this norm into process of scene detection allows considering video as a norm space, which in turn can be transformed to metric space. Difference between the norm values of two consecutive frames is considered as a metric and used to evaluate features of scene changes.

### Main part. Singular value decomposition.

#### Ky Fan norm overview

The use of matrices opens wide possibilities in the application of existing methods and approaches [14-15]. In video processing it is worthwhile to have technique insensitive to the dimension of a source data due to the non-square nature of video frame. Dealing with row matrix allows to reduce computational costs significantly because in this case we can avoid vectorization of a source matrix or transformation into another form like square one for further processing.

On the one hand, descriptors-based approaches allow to reduce dimension of a source data significantly, on the other hand – its calculation still require full processing of video frame. So, having in place meaningful metric retrieved from source data directly rather than vectorized representation allow to skip one step of the processing comparing to traditional approach [16-17].

Moreover, calculations based on the whole frame (or predefined subset of a given matrix) also allow to omit complex step for finding correspondence between received descriptors on two consecutive frames.

Possible technique with such characteristics is singular values decomposition. It allows to use initial matrix without dimension transformations. The SVD of a given matrix  $A \in R^{m \times n}$  is a factorization in the form

$$A = U \Sigma V^T,$$

where:  $U \in R^{m \times m}$  and  $V \in R^{n \times n}$  are unitary matrices, columns of which consist of left- and right-singular vectors of  $A$  respectively;  $\Sigma$  – is a diagonal matrix of a size  $m \times n$  with non-negative diagonal elements denoted as  $\sigma_i, i \in [1, 2, \dots, \min[m, n]]$  which are the singular values of  $A$ . Non-zero  $\sigma_i$  are the square roots of the non-zero eigenvalues of both  $A^T A$  and  $A A^T$ .

More information related to the SVD approach and derivation can be found in [18-21].

Important thing about SVD is that it does not require source matrix to be square which makes it easily applicable for video processing. The point is that support of matrices of any dimension gives flexibility in source data representation. In other words, technical to represent video frames can be based even on source image as well as any composition of descriptors without additional transformations.

In addition, SVD allows reducing dimension of the source data and it positively affects performance of related application. The decomposition expresses original matrix as a linear combination of low-rank matrices so that it can be applied to distinguish static and dynamic part of the video scene. In other words, scene changes can be captured by subtracting the background matrix (approximated with lower rank) from the source one.

Possible way to find matrix with reduced rank is to apply SVD to source matrix and zero out the smallest singular values. Next step is to reconstruct approximated matrix by adjusted components:

$$\widehat{A}_k = U \Sigma' V^T.$$

Open question here is how to determine  $k$ . Singular values can be used to estimate how many components to keep. Standard approach is keeping so many values to explain 85 % of the variation:

$$\frac{\sum_{i=1}^k \sigma_i^2}{\sum_{i=1}^l \sigma_i^2} \times 100 \% \approx 85 \%,$$

where:  $l = \max\{m, n\}$ ;  $\sigma$  – singular value of  $A$  [22].

Meanwhile, choice of reduced rank is a complex task and depends on many aspects like features of a source data, requirements to the result, performance and others. For complex cases can be used progressive algorithms, for example usage of so-called heat maps.

Talking about applying SVD to video segmentation, we need to introduce norm and metric

which would be based on this decomposition so that provide frame representation able to incorporate

It was decided to use Ky Fan k-norm [23] of a matrix  $A \in R^{m \times n}$  as it is built on top of SVD so enables to benefit from all the power of described decomposition. Namely, it is defined as the sum of k largest singular values of this matrix:

$$\|A\|_* = \sum_i^{\min\{m,n\}} |\sigma_i(A)|.$$

The Ky Fan 1-norm, is the same as the operator spectral norm of  $A$ . The last of the Ky Fan norms, also known as nuclear norm, or trace norm, corresponds to Schatten p-norm with  $p = 1$  [24].

Having described Ky Fan norm, we can consider set of video frames as normed space. As we know, every normed space is a metric space and its metric can be defined as  $(x, y) = \|x - y\|$ . In our case distance is a difference between Ky Fan norms of consecutive frames.

**Pros and cons of SVD application.** Decision to use SVD for further investigation was made based on several reasons. This decomposition is built on top of unitary matrices, so its result is valid even if geometrical transformations take place. In other words, result of the decomposition can be easily interpreted for machine learning activities in self-explaining way (for example, rotation and reflection without scaling).

As it was already mentioned, SVD is the most universal approach in terms of source data as it is applicable not only for square or symmetric matrixes (like LU or Cholesky decomposition). SVD does not require elements of the matrix to be nonnegative as for nonnegative matrix decomposition.

Singular decomposition is stable, i.e. small changes in the original matrix correspond to small changes in the matrix  $\Sigma$  and vice versa. In addition, the diagonal matrix  $\Sigma$  makes it easy to understand whether the matrix  $A$  is degenerate. SVD decomposition can be brought or integrated with other methods like non-negative matrix decomposition, can be adapted to improve independent component analysis (ICA) results [25], principal component analysis (PCA) can be expressed by means of matrixes calculated as a part of SVD.

At the same time, the disadvantage is the high computational costs, however, over the long time using SVD, accelerated algorithms for finding it have been developed that are included in the main libraries and are also optimized for use on modern computers.

**Application of Ky Fan norm for video segmentation.** In this section we will consider results produced by developed application. The

image characteristics by means of this mathematical tool.

experiments were carried out for 20 videos with various technical characteristics related to different domains: video from surveillance cameras, modeling of geometric surfaces, animation clip.

First step is to represent source video as a sequence of frames. Then each frame is converted from RGB to grayscale model so that the value of each pixel carries only intensity information. Received matrix of a size  $m \times n$  is applicable for SVD transformation so singular values are calculated. As a result, Ky Fan norm is found for each frame and difference between them is taken.

Now we consider results of Ky Fan norm application for video segmentation for several test videos ( $854 \times 480$ , 27471 kbps). Calculations were made with i7 processor and 32 gb RAM available.

Key frames of the video sequence with the most significant changes and its indexes detected manually and by developed system, are shown on the Fig. 1a and Fig. 1b respectively (for further videos Fig. 2ab and Fig. 3ab). On the Fig. 2a and Fig. 2b (for further videos Fig. 3ab and Fig. 4ab) appropriate fluctuations of the Ky Fan k-norm are presented (first and last norms respectively).

Considering that there are several options how to assign indexes for key frames, in order to simplify understanding, indexes are specified by ranges. It is assumed that within the range scene context is not changed significantly.

**Developed application for scene changes detection.** In order to visualize results of Ky Fan norm usage for video analysis standalone Java application was developed and launched on i5 processor with 16 gb RAM and Ubuntu OS installed.

Oracle Java SE Development Kit 11 was used (latest LTS version). The application has dependencies from three open source libraries with Apache license: commons-math3 for SVD calculation, org.bytedeco for converting video into sequence of images and Apache Open Office API for charts creation.

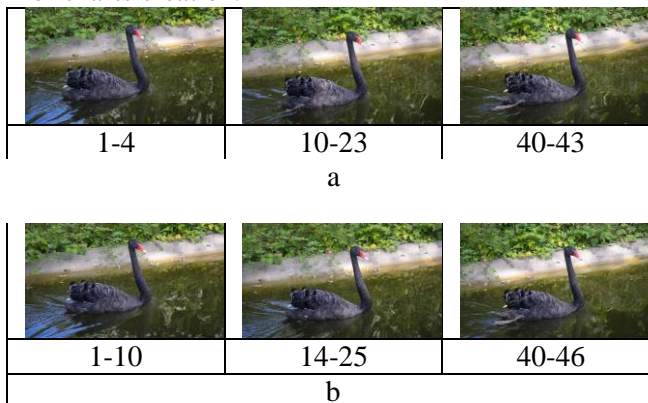
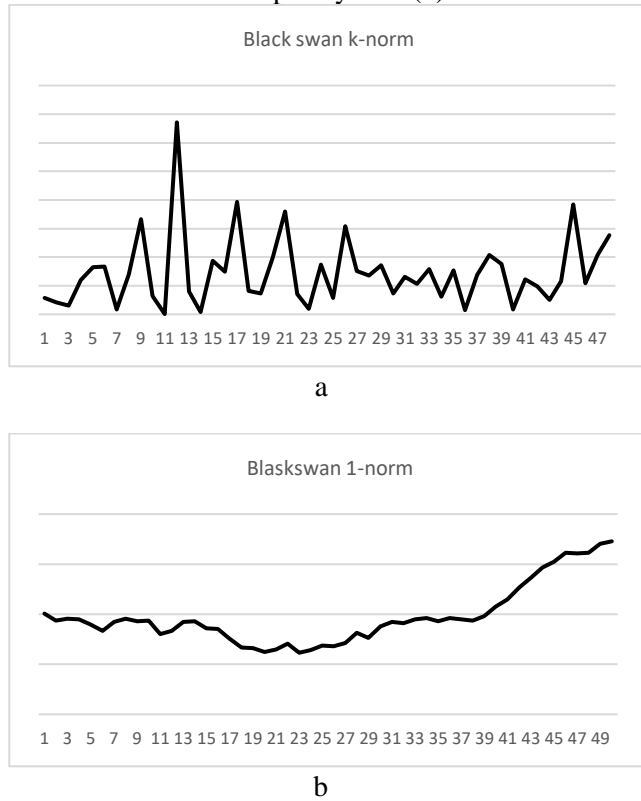


Fig. 1. Key frames detected manually (a) and by the developed system (b)



normalization or results smoothing in order to distinguish features of the context.

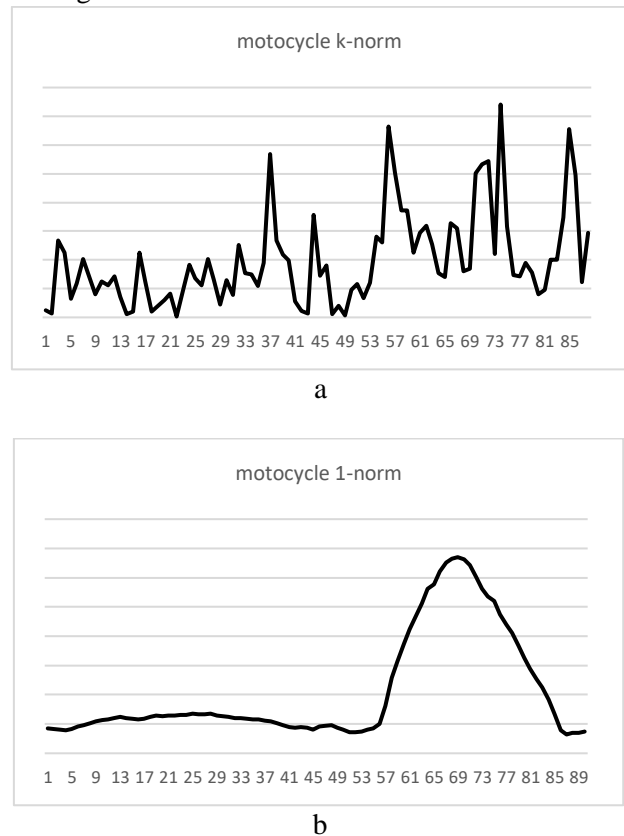


Fig. 2 Ky Fan norm fluctuations for k-norm (a) and 1-norm (b)

Fig. 4 Ky Fan norm fluctuations for k-norm (a) and 1-norm (b)

1-29	36-45	60-70	82-89
a			
1-30	37-60	60-70	80-90
b			

Fig. 3. Key frames detected manually (a) and by the developed system (b)

In contradistinction to previous video, this test data contains significant scene changes and it is reflected in the absolute value of the received Ky-Fan norm. For second experiment it is several times greater than in previous case. Next step here is to investigate correlation between context of the video and corresponding norm value to identify thresholds of method sensitivity. Based on initial results, possible option can be to provide

**Conclusions.** This paper contains description of the results received for applying Ky-Fan norm for video segmentation. As a part of this prove of concept SVD application to video segmentation whole video frame converted to grayscale model was taken as a matrix for singular value decomposition. Based on retrieved singular values Ky Fan 1-norm and k-norm were calculated in order to detect scene changes.

Computations show that Ky Fan norm is capable to reflect frame changes and it is proportional to scene changes. In other words, the more difference between images is, the bigger absolute value of the norm is. Open question and appropriate next step here is to investigate how to determine nature of video context changes based on the calculated value.

It is also proved that 1-norm reflects bigger changes than k-norm so it can be used for cases when only significant changes are point of the interest. For cases when it is required to detect even small diversity between images Ky Fan k-norm is a better option.

For further investigation it is also important to Namely, it is planned to calculate region-based Ky Fan norm instead of for whole image. Such approach is expected to detect smaller changes of the video context and is more effective from performance point of view as allows parallelization of computing.

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## ВИКОРИСТАННЯ НОРМИ КІ ФАН ДЛЯ ВИРІШЕННЯ ЗАДАЧІ СЕГМЕНТАЦІЇ ВІДЕОПОТОКУ

**Анотація:** У даній статті розглянуто результати застосування норми Кі Фана у контексті рішення задачі сегментації відеоданих. Оскільки задача аналізу відео зводиться до аналізу послідовності зображень, було прийнято рішення знайти спосіб формалізації опису відеокадру з використанням математичного апарату неквадратних матриць. При виборі методу ретельна увага приділялася саме універсальності по відношенню до розмірності вихідних даних, зважаючи на технічні характеристики відеоданих - відеокадри є матриці довільної розмірності. Можливість пропустити крок приведення матриці до квадратної, або векторизації за допомогою деякого дескриптора дозволяє знизити обчислювальні витрати, визволяючи ресурси, необхідних для цього перетворення. Було прийнято рішення використовувати в якості дескриптора зображення значення норми Кі Фана, оскільки вона побудована на основі сингулярних чисел матриці. Як відомо, сингулярні числа отримуються в ході сингулярного розкладання матриці і можуть бути використані для зниження розмірності вихідних даних. Сингулярний розклад не має обмежень ні до розмірності ні до характеру елементів вихідної матриці. Крім того, він може бути використан для приведення до інших матричних розкладань, що мають необхідні характеристики. Був проведений порівняльний аналіз ефективності отриманого дескриптора в разі використання k-норми і l-норми, який показав, що l-норма дозволяє виявляти найбільш суттєві зміни сцени, в той час як k-норма здатна детектувати і незначні. Іншими словами, в залежності від характеру вихідних відеоданих та сфери застосування розробленого додатку, є можливість задавати чутливість до зміни сцени, варіюючи кількість задіяних

сингулярних чисел. Рішення про наявність змін в контексті сцени відеокадру приймається на основі порівняння дескрипторів, тобто значення норми  $K_i$  Фана, двох послідовних зображень.

**Ключові слова:** сегментація відеопотоку; норма  $K_i$  Фан; сингулярний розклад матриці  
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## ИСПОЛЬЗОВАНИЕ МЕТРИКИ $K_i$ ФАН В КОНТЕКСТЕ ЗАДАЧИ СЕГМЕНТАЦИИ ВИДЕОПОТОКА

**Аннотация:** В данной статье представлены результаты применения нормы  $K_i$  Фан в контексте решения задачи сегментации видеоданных. Поскольку задача анализа видео сводится к анализу последовательности изображений, было принято решение найти способ формализации описания видеокадра с использованием математического аппарата неквадратных матриц. При выборе метода особое внимание уделялось именно универсальности по отношению к размерности исходных данных ввиду технических характеристик и природы видеоданных – видеокадры представляют собой матрицы произвольной размерности. Возможность пропустить шаг приведения матрицы к квадратной, либо векторизации с помощью некоторого дескриптора, позволяет снизить вычислительные расходы, освобождая ресурсы, необходимые для этого преобразования. Было принято решение использовать в качестве дескриптора изображения значение нормы  $K_i$  Фана, поскольку она построена на основе сингулярных чисел матрицы. Как известно, сингулярные числа вычисляются в ходе сингулярного разложения матрицы и могут быть использованы, в числе прочего, для снижения размерности исходных данных. Сингулярное разложение не налагает ограничений ни на размерность ни на характер элементов исходной матрицы. Кроме того, оно может быть использовано для приведения к другим матричным разложениям, обладающими необходимыми характеристиками. Был проведен сравнительный анализ эффективности полученного дескриптора в случае использования  $k$ -нормы и  $1$ -нормы, который показал, что  $1$ -норма позволяет выявлять наиболее существенные изменения сцены, в то время как  $k$ -норма способна детектировать и незначительные. Другими словами, в зависимости от характера исходных видеоданных и сферы применения разработанного приложения, есть возможность задавать чувствительность приложения к изменению сцены, варьируя количество задействованных сингулярных чисел. Решение о наличии изменений в контексте сцены видеокадра принимается на основе сравнения дескрипторов, то есть значения нормы  $K_i$  Фана, двух последовательных изображений.

**Ключевые слова:** сегментація відеопотока; норма  $K_i$  Фан; сингулярне розкладження матриці



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