KARHUNEN-LOEVE ANALYSIS OF DYNAMIC SEQUENCES OF THERMOGRAPHIC IMAGES FOR EARLY BREAST CANCER DETECTION

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ABSTRACT

The Karhunen-Loève transform (KLT) is applied to the analysis of dynamic sequences of thermograms describing the temporal evolution of the body surface temperature following the application of a external thermal stimulus. The KLT may be evaluated either along the spatial or temporal dimensions of the data; the duality of both representations is emphasized. An example is presented to illustrate that the KLT allows an efficient data reduction and facilitates tumor detection by highlighting physiologically important abnormalities in the time behavior of thermal patterns.

I. INTRODUCTION

Although static infrared (IR) thermography has a number of attractive properties for its practical application in mass screening, some fundamental limitations have cast serious doubts in the medical world as to its value for tumor detection [1]. To reduce some of these drawbacks, a dynamic method for medical IR thermography has been described recently, and has been shown to be more reliable for early breast cancer detection [2]. This technique starts with microwave irradiation which is intended to induce a differential heating between healthy and tumor tissues.The temperature distribution during relaxation to thermal equilibrium is then recorded, resulting in a characterization that is richer than that of conventional thermography.

To facilitate the interpretation of a dynamic sequence of thermograms and to reduce the amount of data, it seems advantageous to uses digital image processing techniques. This paper describes the application of the Karhunen-Loève transform (KLT) to this particular problem. This method is used because it is optimal for data compression. It is also closely related to factor analysis [3], and, as such, should be capable of extracting patterns related to physiological or physical characteristics. Similar techniques have been applied previously to the analysis of dynamic sequences in medical imaging [4]. However, the decomposition has always been performed by considering the temporal signals associated with each pixel. An important point that we want to make here is that the KLT can also be applied in the spatial domain, and that both temporal and spatial decompositions are dual representations. The use of centered variables is also conceivable but the normalization with respect to the average signal, which is either defined in time or in space, is not equivalent in both representations. In the spatial approach, standardization with respect to the average image has the advantage of allowing a clear separation between dynamic and static image components.

II. DATA COLLECTION AND PREPROCESSING

A. Dynamic thermography

This technique involves the study of the evolution of the thermal distribution on the skin after application of a thermal stimulus [2]. The stimulus is induced by microwave heating (frequency : f=2.45 GHz, irradiation time : t=2min; power density : P= 80 to

100 mW/cm²) combined with active convective cooling of the skin to reduce excessive heating of the subcutaneous fat layer. The microwave radiation produces a higher heating rate of tumors in comparison to healthy tissues, mainly due to differences in dielectric constant, density, specific heat, and vascularisation. Following the heating period, thermograms are acquired every 30s using an infrared camera (AGA 680) connected to a video digitizer. At the end of a session of approximately 8min, the evolution of the thermal distribution is described by a sequence of about 16 (N) digital images of 512x512 pixels with 8 bits per pixel, which may then be analyzed using image processing techniques.

Based on experiments on phantoms, Wistar rats and humans, it appears that the dynamic approach is superior to conventional static thermography in revealing the presence of malignant disease, even without digital image processing [2]. This new method has the ability to detect deeper lying and smaller tumors. It also has the advantage of allowing shorter thermographical sessions, and of being less sensitive to environmental conditions.

B. Preprocessing

The major problem with our data acquisition system is that the structures of interest may be subject to small displacements from one time frame to another, due to respiration and accidental movement of the patient. To compensate for this effect, a rectangular window is specified interactively to extract a breast (right or left) on an image of the sequence, which typically displays the whole chest of the patient. This sub-image is used as a reference template and is correlated with the remaining images of the sequence within a range of a few pixels in each direction. A sequence of aligned breast images is generated by selecting the sampling window position that maximizes the correlation value. This processing, which is applied to each breast separately, compensates efficiently for global translational movements and has been found to be adequate in most cases.

For improved robustness, the reference sub-image is usually extracted from the central image in the sequence. The measure of goodness of fit is chosen as the normalized correlation coefficient, which is invariant under global amplitude and baseline variations.

III. THE KARHUNEN-LOEVE TRANSFORM

The use of the KLT for the analysis of thermographic data is justified for two main reasons. First, the KLT is optimal for linear data reduction. It allows the compression of an initial sequence of N images into a small number $N' \leq N$ of eigen-images with their associated weights along the time dimension. These eigen-images contain almost all relevant dynamic and static information and should be easier to interpret or process in order to detect abnormalities. By removing the components with lesser contributions, one also reduces noise. Second, the KLT is closely related to factor analysis [3]. It provides an easy way to estimate factors that may be related to physiological or physical characteristics. Our analysis can be performed by using either one of the following representations of our data, which globally consists of N images of M pixels each.

A. The spatial Model

Let the sequence of preprocessed thermograms be represented by the collection of M-dimensional vectors $\{\boldsymbol{x}_k, K=1,\ldots,N\}$, obtained by re-arranging the pixels in an image sequentially. We consider the expansion :

$$\boldsymbol{x}_k = \sum_{n=1}^{N'} a_n^{<k>} \boldsymbol{u}_n + \boldsymbol{n}_k \qquad (1)$$

where $N'<N$, which decomposes our data in a structural part plus a residual noise component $\boldsymbol{n}_k$. The vectors $\boldsymbol{u}_i$, $i=1..N'$, represent certain intrinsic spatial characteristics (or components) of the data that appear with different weights in time. The coefficients of the model are the time functions : $\{a_n^{<k>}, k=1,\ldots,N\}$, $n=1,..,N'$.

The KLT is used to determine the structural part of this model by minimizing the variance of the residual noise component and by producing orthogonal spatial factors. The $\boldsymbol{u}_n$'s are computed as the eigenvectors of the spatial MxM scatter matrix ($\boldsymbol{X}\boldsymbol{X}^T$), where $\boldsymbol{X}$ is the MxN data matrix $\boldsymbol{X} = [\boldsymbol{x}_1 \ldots \boldsymbol{x}_N]$. The rank of ($\boldsymbol{X}\boldsymbol{X}^T$) is less than or equal to N, which implies that there are at most N non-zero eigenvalues $\{\lambda_n, n=1,..N\}$.

B. The temporal Model

Alternatively, we may also consider the time-series associated to every spatial location, which we represent by the set of N-dimensional vectors : $\{\boldsymbol{y}_i, i=1,..,M\}$. We now assume a temporal model :

$$\boldsymbol{y}_i = \sum_{n=1}^{N'} b_n^{<i>} \boldsymbol{v}_n + \boldsymbol{n}_i' \tag{2}$$

where $\boldsymbol{n}_i'$ is an N-dimensional noise signal and where the $\boldsymbol{v}_n$'s are time functions representing different intrinsic heating or cooling characteristics. The coefficients of the model, $\{b_n^{<i>}, i=1,..M\}$ with $n=1,..,N'$, are spatial weights which measure the specific contribution to any of those factors at a given position i.

To determine the components of this model, we may use the KLT in very much the same way as for the spatial representation. The $\boldsymbol{v}_n$'s are chosen as the eigenvectors of the NxN temporal scatter matrix (or spatial inner-product matrix) $(\boldsymbol{YY}^T) = (\boldsymbol{X}^T\boldsymbol{X})$, where $\boldsymbol{Y}=[\boldsymbol{y}_1 \dots \boldsymbol{y}_M]$. The eigenvalues of the matrix are $\{\lambda_n', n=1,...,N\}$.

C. Dual KLT expansions

The KLT expansions associated with Eq.(1) and (2) are dual representations. By using the characteristic equations $(\boldsymbol{XX}^T)\boldsymbol{u}=\lambda\boldsymbol{u}$ and $(\boldsymbol{X}^T\boldsymbol{X})\boldsymbol{v}=\lambda'\boldsymbol{v}$, it is straightforward to demonstrate the following properties, which allow the determination of one representation from the other.

Property 1 : The scatter matrix $\boldsymbol{XX}^T$ and the inner-product matrix $\boldsymbol{X}^T\boldsymbol{X}$ have an identical set of non-zero eigenvalues : $\lambda_1, ..., \lambda_{N'}$, where $N' \leq \min(M,N)$.

Property 2 : The corresponding eigenvectors $\{\boldsymbol{u}_n\}$ and $\{\boldsymbol{v}_n\}$ are related by the relationships :

$$\boldsymbol{v}_n = \boldsymbol{X}^T.\boldsymbol{u}_n / \sqrt{\lambda_n}, \quad (n=1,....,N') \tag{3}$$

$$\boldsymbol{u}_n = \boldsymbol{X}.\boldsymbol{v}_n / \sqrt{\lambda_n}, \quad (n=1,....,N') \tag{4}$$

In our case where N is much smaller than M, it is computationally more advantageous to determine the spatial expansion by diagonalizing the inner product matrix $(\boldsymbol{X}^T\boldsymbol{X})$ and to use Eq.(4) to compute the eigen-images $\{\boldsymbol{u}_n\}$, which is a procedure initially suggested by McLaughlin [5]. In addition, we can show that the coefficients of the spatial model $\{a_n^{<k>}\}$, represented by a N'xN coefficient matrix $\boldsymbol{A}=[\boldsymbol{a}_1 \dots \boldsymbol{a}_N]$, may be simply determined by

$$\boldsymbol{A} = [\boldsymbol{a}_1 \dots \boldsymbol{a}_N] = [\sqrt{\lambda_1}\, \boldsymbol{v}_1 \dots \sqrt{\lambda_{N'}}\, \boldsymbol{v}_{N'}]^T \tag{5}$$

All these equations indicate that there is a one-by-one relationship between $\boldsymbol{u}_n$ and $\{b_n^{<i>}\}$, and $\{a_n^{<k>}\}$ and $\boldsymbol{v}_n$, respectively, which is a simple normalization by the square-root of the corresponding eigenvalue. Therefore, the spatial or temporal KLT expansions are essentially equivalent. The only difference is in the interpretation of the results which depends on the underlying model.

A natural extension of these techniques is to consider centered or standardized variables, which is obviously not equivalent in both formulations. For our application, we have deliberately chosen to standardize the data with respect to the average image to distinguish between the static and dynamic image components. This normalization favours a spatial interpretation of the results.

IV. RESULTS

We present results obtained for a patient with a positive diagnosis of cancer in the left breast. The sequences of aligned left and right breast images were extracted from the original thermograms using the technique outlined in section 2.B. These sub-images are shown in Fig. 1. The average image (or static component) of both sequences were computed and are displayed in Fig. 2-A. A comparison between these pictures reveals that the left breast is hotter than the right one. The average image was then subtracted from each individual image in the sequence in order to concentrate on the dynamic behavior of the data exclusively. The Karhunen-Loève analysis was performed on these reduced variables using the algorithm described in section 3.C. For each breast, the first three eigen-images and their corresponding temporal weights are shown in Fig. 2-C. In both cases, the first components account for more than 80% of the energy of the dynamic component. The effect of

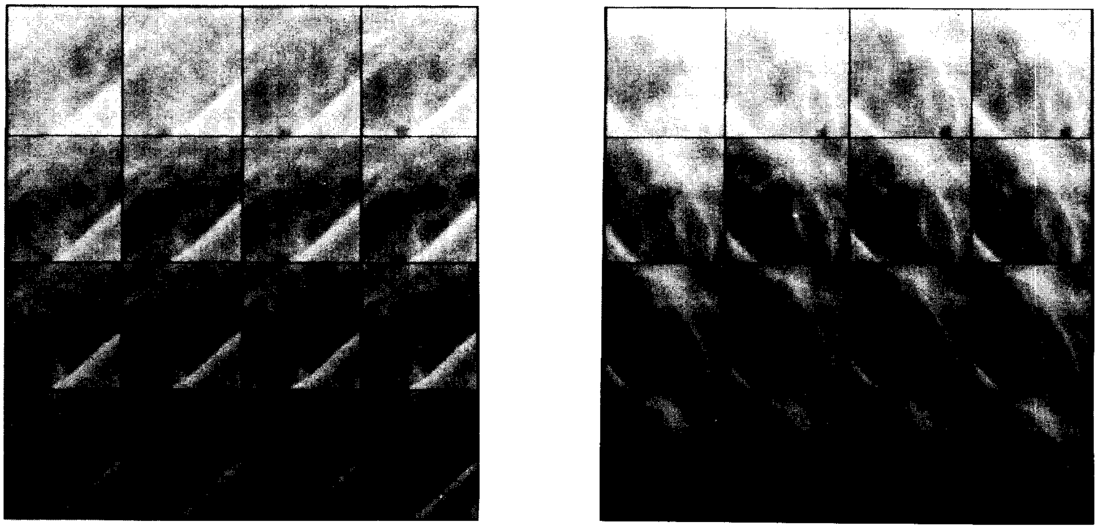

Fig. 1 : Sequences of 12 aligned sub-images for the right and left breast of the patient.

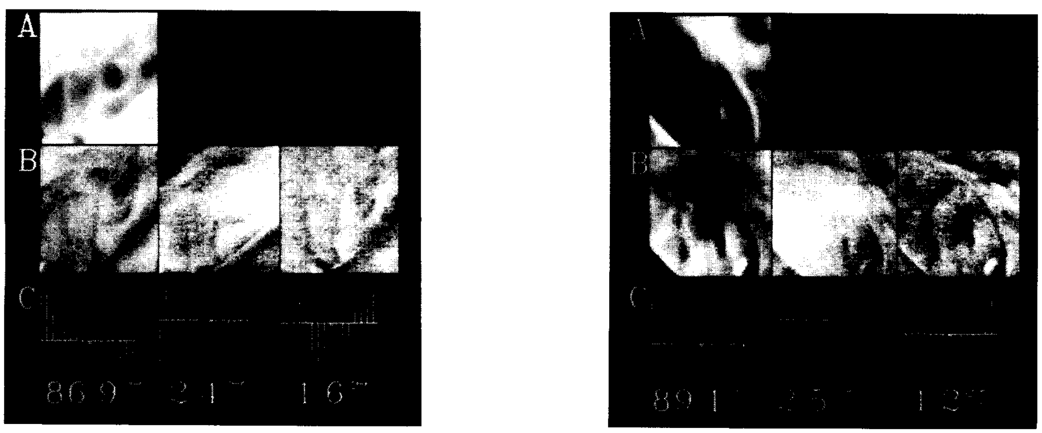

Fig. 2 : Results of KLT analysis for the right and left breast. (A): mean images; (B): first three eigen-images corresponding to the most significant eigenvalues; (C): temporal weights.

movement is slightly visible in some components but has been substantially reduced by preprocessing. The lower components, which are not all shown here, are mainly due to noise. The first eigen-component of the right breast has a nearly homogeneous greyvalue, while the one associated to the left breast has a abnormally dark region in the upper right part of the image, indicating a strong difference in the dynamic cooling between this area and the background. This area which is marked by an arrow corresponds to the exact location of the tumor. The phenomenon that is visualized on this image is purely dynamic and supports the fact that the additional (non-static) information measured by dynamic thermography is particularly relevant for tumor detection.

The examination of the sequence of time coefficients corresponding to the different eigen-images is also informative. For both breasts, the first of these sequences are rather smooth decreasing functions of time that may be interpreted as cooling characteristics. It follows that the brighter regions in the first eigen-images are the ones that cool down the most rapidly while the darker ones (smaller values) are the ones that lose less heat. Thus, a possible interpretation of the predominant factor is that of a measure related to the time constant or to the slope of the temperature law as a function of the spatial position.

For comparison, the KLT was also performed with no mean subtraction with results comparable to those obtained above. The static image components were almost completely extracted by the first eigenvectors and the corresponding eigen-images were very similar to the averages displayed in Fig. 2-A. The second eigen-images were similar to the first eigen-components displayed in Fig.2-B, with the difference that the corresponding sequences of time weights were not nearly as smooth as those shown in Fig. 2-C.

V. CONCLUSION

The conclusion of this study is that the analysis of a dynamic sequence of thermograms can be performed efficiently by decomposing it into two main components. The first one represents the static information that is common to most images and is most naturally measured by the average image of the sequence. The second component is extracted by means of the Karhunen-Loève transform and explains a relatively large portion (~85%) of the dynamic variation. The first advantage of this approach is a substantial data compression. The second is that of an alternative data representation which emphasizes important aspects of the time behavior of the thermal patterns and greatly facilitates tumor detection.

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