been great results. The use of laser Doppler techniques and laser speckle techniques is well known in the noninvasive investigation of microcirculatory blood flow. A non-invasive optical technique would have advantages both for a patient (no injection of potentially damaging chemicals) and for scientists and physicians.

Laser Doppler measures the total local microcirculatory blood perfusion including the perfusion in capillaries (nutritive flow), arterioles, venules and shunting vessels. The technique is based on the emission of a beam of laser light carried by a fiber-optic probe.

The light is then scattered and partly absorbed by the tissue being studied. Light hitting moving blood cells undergoes a change in wavelength (Doppler shift) while light hitting static objects is unchanged. The magnitude and frequency distribution of these changes in wavelength are directly related to the number and velocity of the blood cells in the sample volume. The information is picked up by a returning fiber, converted into an electronic signal and analyzed. The measuring depth depends on tissue properties such as the structure and density of the capillary beds, pigmentation, oxygenation, etc. It also depends on the wavelength of the laser light, and on the distance between the sending and receiving fibers in the laser Doppler probe. Many workers have used the Doppler approach to measure blood flow and the technique is now almost a routine tool in medicine.

Laser speckle is an interference pattern produced by light reflected or scattered from different parts of the illuminated surface. When an object moves, the speckle pattern it produces changes. For small movements of a solid object, the speckles move with the object, i.e., they remain correlated. This has been exploited in a technique known as «double-exposure speckle photography». By scanning the laser beam across the speckle pattern, a map of local movements can be built up.

The experimental setup for laser speckle contrast imaging is very simple. Diverging laser light illuminates the object under investigation, which is imaged by a CCD camera (or equivalent). The image is captured by a frame grabber (or equivalent) and the data passed to a personal computer for processing by custom software. The operator usually has several options at his disposal.

If the object under investigation contains moving scatterers, such as blood cells, each speckle will be fluctuating in intensity. A time-integrated image therefore shows a reduction in speckle contrast because of the averaging of the intensity of each speckle over the integration time. In practice, the exposure time can be very short, typically 0,02 seconds, and the processing time is less than one second for the whole frame making it effectively a real-time technique.

It can be shown, however, that the two techniques yield the same mathematical formula connecting the frequency of the fluctuations and the velocity of the scatterers – they are simply two different ways of looking at the same phenomenon. The main principles of two different methods of noninvasive investigation microcirculation parameters have been outlined.

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DIMENSIONALITY REDUCTION FOR PATTERN RECOGNITION SYSTEM

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For nearly a century, researchers have investigated and used mathematical techniques for reducing the dimensionality of vector valued data used to characterize categorical data with the goal of preserving “information” or discriminability of the different categories in the reduced dimensionality data.

Pattern recognition deals with mathematical and technical aspects of classifying different objects through their observable information, such as grey levels of pixels for an image, energy levels in frequency domain for waveform and the percentage of certain contents in a product. Conventional pattern recognition systems have two components: feature analysis and pattern classification, as shown in Fig.1.

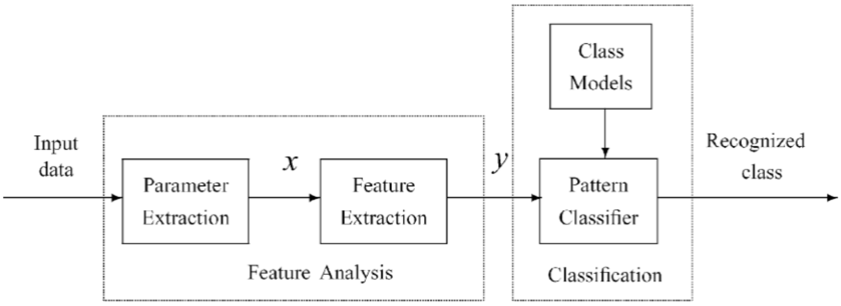

Fig. 1. Conventional pattern recognition system.

Feature analysis is achieved in two steps: parameter extraction step and feature extraction step. In the parameter extraction step information relevant for pattern classification is extracted from the input data in the form of a *p*-dimensional parameter vector *x*. In the feature extraction step, the parameter vector *x* is transformed to a feature vector *y*, which has a dimensionality *m* ($m \leq p$).

Feature extraction can be conducted independently or jointly with either parameter extraction or classification. LDA (Linear Discriminant Analysis) and PCA (Principal Components Analysis) are the two popular independent feature extraction methods. Both of them extract features by projecting the original parameter vectors into a new feature space through a linear transformation matrix. But they optimize the transformation matrix with different intentions.

Principal Components Analysis (PCA), also known as the Karhunen-Loeve Transform (KLT), has been known of and in use for nearly a century, as a linear method for dimensionality reduction. Operationally, PCA can be described as follows: Let $X = [[x_1, x_2, \dots, x_n]]^T$ be an n -dimensional (column) feature vector, and $Y = [[y_1, y_2, \dots, y_m]]^T$ be an m -dimensional (column) feature vector, obtained as the linear transform of X , using the n by m transformation matrix *A*, i.e. *Y*=A^T *X*. Let $\hat{X} =$ *BY* be an approximation to *X*. Note that *X,Y* and $\hat{X}$ can all be viewed as (column) vector-valued random variables. The goal of PCA is to determine A and B , such that $E\left\{(X - \hat{X})^2\right\}$ is minimized. That is, $\hat{X}$ should approximate X as well as possible, in a mean square error sense.

Linear transforms for the purpose of reducing dimensionality while preserving discriminability between pre-defined categories have also long been known about and used, and are usually referred to as Linear Discriminant Analysis (LDA). The mathematical usage of this is identical to that for PCA. That is $Y = A^T X$, where X, Y are again column vectors as for PCA. The big difference is in how A is computed. For LDA, it has been shown that the columns of A correspond to the m largest eigenvalues of $S_W^{-1} S_B$, where S_W is the within class covariance matrix and S_B is the between class covariance matrix.

Though PCA and LDA are commonly used for feature dimension reduction, both of them have their own advantages and disadvantages. PCA is relatively easy to implement, since the matrix used in eigen-decomposition is always non-singular. This is not the case for LDA. However, the discriminant information may not reside in the direction with large component variance. That is the weakness of PCA and where LDA shines. Since PCA and LDA are two complementary techniques, PCA/LDA combined method show better results than single PCA and LDA classifiers.

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