Normalised

If the two image regions are feeble variations of the same scene, then the heuristic [5] change has little effect. This technique has numerous applications like MRI Image Section Matching and RGB Color Image Matching

Image matching method based on grey value is widely used in various fields, such as medical image

analysis, video processing, traffic control, etc. One of the most commonly used algorithms is

normalized cross-correlation algorithm (normalized cross correlation, NCC). The main advantage of

the NCC algorithm is less sensitive to the linear change of light intensity, better anti-jamming ability.

, which is easy to set up detection threshold. However,

NCC algorithm is calculated through per-pixel, which leads to large amount of calculation. The speed

of NCC algorithm is slow. It is only suitable for the occasion of the processing, when speed

requirement is not high. Many fast NCC algorithms have been put forward, such as quickly NCC

algorithm based on sum tables, fast algorithm based on winner update strategy, successive elimination algorithm, and the theory of chunking bounded partial correlation, etc. Matching algorithm need to speed up the matching speed effectively. In order to solve these problems, a new normalized cross-correlation matching algorithm based on the characteristics of templates and matching image is presented in this paper. And the algorithm can speed up the image matching.

* Convolution is correlation with the filter rotated 180 degrees. This makes no difference, if the filter is symmetric, like a Gaussian, or a Laplacian. But it makes a whole lot of difference, when the filter is not symmetric, like a derivative.
* The reason we need convolution is that it is associative, while correlation, in general, is not. To see why this is true, remember that convolution is multiplication in the frequency domain, which is obviously associative. On the other hand, correlation in the frequency domain is multiplication by the complex conjugate, which is not associative.
* The associativity of convolution is what allows you to "pre-convolve" the filters, so that you only need to convolve the image with a single filter. For example, let's say you have an image ff, which you need to convolve with gg and then with hh. f∗g∗h=f∗(g∗h)f∗g∗h=f∗(g∗h). That means you can convolve gg and hh first into a single filter, and then convolve ff with it. This is useful, if you need to convolve many images with gg and hh. You can pre-compute k=g∗hk=g∗h, and then reuse kk multple times.

As seen in figure 3.2 any data can be represented as a cobination of sinwaves. For this reason, spectral cross correlation can be performed to align 2 \mathrm{D} inages as there is no problem converting 2 \mathrm{D} inputs into the Frequency dotnain.

* + A Fourier transform is a signal processing technique which decomposes a function on the time domain into a function in the frequency domain. Since we are working with cyclic data it is appropriate to incorporate Fourier transforms
* DFT/FFT
  + However, the transform involves continuous integrals but in practice computers and digital processing systems can only work with ﬁnite sums. This problem is over come by making use of a fast Fourier transform (FFT) which is an algorithm that computes the discrete Fourier transform [9].
* So if you are doing [template matching](http://en.wikipedia.org/wiki/Template_matching), i. e. looking for a single template, correlation is sufficient. But if you need to use multiple filters in succession, and you need to perform this operation on multiple images, it makes sense to convolve the multiple filters into a single filter ahead of time

Fourier methods are commonly used for signal analysis and system design in modern telecommunications, radar, and image processing systems. Classical Fourier methods such as the Fourier series and the Fourier integral are used for continuous time (CT) signals and systems, i.e., systems in which a characteristic signal, s(t), is defined at all values of t on the continuum -\infty<t<\infty. A more recently developed set of Fourier methods, including the discrete time Fourier transform (DTFT) and the discrete Fourier transform (DFT), are extensions of basic Fourier concepts that apply to discrete time (DT) signals. A characteristic DT signal, s[n], is defined only for values of n where n is an integer in the range -\infty<n<\infty. The following discussion presents basic concepts and outlines important properties for both the \mathrm{CT} and \mathrm{DT} classes of Fourier methods, with a particular emphasis on the relationships between these two classes. The class of DT Fourier methods is particularly useful

* Lossy versus lossless comporession - using a filter for the lowest amplotude
  + - FR:
    - DFT 1D/2D (flow chart and explanation)
    - However, the transform involves continuous integrals but in practice computers and digital processing systems can only work with ﬁnite sums. This problem is over come by making use of a fast Fourier transform (FFT) which is an algorithm that computes the discrete Fourier transform [9].

Depth map

For a normal user with a 2D digital camera, 3D images may be constructed by extracting the depth information from 2D images using a variety of techniques proposed over the past [4]–[8].

Depth maps are generated generally from a 2D set of images Among these methods, depth-map generation from a stereo pair of images is the most popular one [9]–[15]. It finds many of its applications in 3D imaging [16] , decoding light field images [17], hand tracking [18] etc. Essentially, a depth-map is a Grey-coded 2D image that gives the perception of depth by the intensity of colors. This paper presents an algorithm for the creation of depth-map starting from a stereo pair of images i.e left (L–) and right (R–) images corresponding to the same scene by performing a pixel-to-pixel matching. The algorithm finds matching pixels by comparing the RGB components of the pixels in the L– and R–images. If the dissimilarity between the compared pixels is found to be less than a pre-specified tolerance (user defined) then those pixels are considered by the algorithm as a ‘matching pair’ of pixels. Binocular disparity is then calculated for the matched pixels which is further utilized to estimate depth information.

This section discusses various approaches for generation of depth-maps. Some of them are supervised and others are unsupervised. A MATLAB algorithm was developed to construct depth mask using two static images [13]. The algorithm displays the two images and the user matches corresponding points in both images. From the displacement of the selected image points the algorithm estimates a depth surface for the scene. It is a supervised approach, here user interaction is required for point matching [13]. An approach which is based on both monocular and stereo cues was proposed for estimating depth [19]. In their work they apply a Markov Random Field (MRF) learning algorithm to capture monocular cues and then combine them with stereo cues to obtain depth maps. However some of these monocular cues are based on prior knowledge, which requires supervised learning [19]. To detect depth discontinuities from a stereo pair of images, an algorithm was presented that matches individual pixels in corresponding scan-line pairs, while allowing occluded pixels to remain unmatched, then propagates the information between

A depth map is a 2D image that gives the depth (with respect to the viewpoint) of an object as a function of the image coordinates.

Usually, it is represented as a Grey level image with the intensity of each pixel registering its depth. The tasks required for creation of Depth-map are: (i) Capturing Images, (ii) Image Preprocessing, (iii) Depth Estimation, and (iv) Calculation of color value for all pixels. A. Capturing Images. Read both images byte by byte and store them. Separate RGB (Red, Green & Blue) components of each pixel. C. Depth Estimation Depth estimation is the calculation of depth of different objects in a scene from a multiple views or images.