Volume : 3 | Issue : 10 | October 2014 • ISSN No 2277 - 8179

Research Paper

Robust Image Normalization Using H-Connection Technique for Face Recognition

Computer Science

KEYWORDS : Image Quality, Normalization, pixel Coordination, image reconstruction

K.M.Ponnmoli	Research Scholar, PRIST University, Thanjavur, TamilNadu, India.
Dr. S. Selvamuthukumaran	Director, Department of Computer Applications, Mannampandal, TamilNadu, India.

ABSTRACT

Normalization process for face recognition process is a vital one that can be done by perform the H-connection of pixel coordinates from badly degraded face images are very confronting tasks because of high variation between the image background and the foreground layers of different document images. In this proposed system the novel image normalization using the H-CON (Hierarchical Connection) technique handle these issues with the adaptive image contrast. Combination of the local image contrast and the local image gradient constitutes the adaptive image contrast. It is adaptive to the variation of text and background with the image degradation. In the proposed system the map is first developed for the degradation of the image.

The contrast map is then binarize and it is integrated with the Canny's edge map to recognize the pixel edges. The feature of the image is divided by a threshold and it is determined with the intensities in the pixel edges. In the proposed system the method is clear and strong and includes minimum boundary tuning. The experiments on the test bed has a several challenging tasks and documents .Estimated with other techniques shows the PSNR,FAR and noise level of the output image.

1. INTRODUCTION

Bilinear interpolation are known with the filtering linear filtering operations on a given image, and the support and coefficients are made up of top-down assumptions, e.g., polynomial image. For natural images the deduction is not true. Learning is done on the real image data. Possibly, learning-based approaches are efficient and it has better production than top-down strategies [1]–[3]. In principle, a learning based filter design can use arbitrary size support. Bilinear interpolator manipulates the four low-resolution pixels when deciding the pixel value in the high-resolution image. To intercept the over fitting the support is simple for the images. The disadvantage is simple ones will fail to seize the important information restrained in the pixels. The concentration of the support is useful when we need high-quality image interpolator in digital cameras and mobile phones. In this method, the tradeoff is calculated for high quality and low cost.

In our composition, each pixel is replaced in a low-resolution of face images by a high-resolution images from the ORL database. Of course from one pixel value it is impossible to approximate the pixels. For every pixel the local interpolation is repeated and the image is established by decorating the high-resolution patches. Vector value is mapped from low-resolution patch to a high-resolution patch. We label the problem of regulating the supports by originating the image interpolation from a opinion of sparse Bayesian estimation[4][5]. Optimal shape is determined to perform the discrete optimization which compares the different shapes of support.

Otherwise, sparse Bayesian method is important for regulating the pixel. For high resolution patches less needed low resolution are automatically decreased. The learning of filter coefficients has been examined by Triggs [6][7][8], reducing computing, and by Atkins [1], called as resolution synthesis (RS), used for expansion of the image. In [8], the interpolator is learned and the original images are smoothed, sample images have a possible estimation. Riggs suggested the shape favor the sin function. He found interpolation of test factor is remarkable. Atkins RS has a Gaussian mixture deploying the expectation-maximization (EM) algorithm. NI and Nguyen [9] suggested RS by restoring the linear and non linear interpolators. Super resolution method can be observed as RS and also it carries the information from the training data rather than the given image.

2. LITERATURE REVIEW

2.1 Classification-based methods in optimal image interpolation

Two new approaches are introduced for optimal image. This optimal image is consists of different categories and classes with the edges of smooth gradients. The pixel is interpolated by classifying the image data in the window. The interpolation filter is originated for selected class. The designed is based on two methods. First method is called Resolution Synthesis (RS)[9].It has computing capabilities in a Gaussian mixture model. Second method is called as Tree based Resolution (TRS)[10], regression tree is performed in this method. By training the sample images the parameters are estimated. The methods are based on stochastic models and the Mean-Squared error is calculated and the demand is minimum. For many applications in image processing, it is necessary to interpolate digital image data in order to render the same image at a higher resolution. An example of such an application is printing, where one has source image data at a fixed resolution, but would like to print it at a higher resolution.

Enhanced tree based RS made up of TRS Interpolation .In the enhancement stage the pixels are added in the interpolated stage. . The objective in RS is to compute the minimum mean-squared error estimate of the high-resolution image, given the low-resolution image. For this, we use a stochastic model which explicitly relates vectors containing source image data to corresponding vectors of target-resolution image data. While transmitting at the sharpening stage the interpolation effects are reduced. RS are trained with the excessive quality of interpolation images. Examples are said to be digital camera images and JPEG images. New coding method is introduced with the JPEG compression scheme. As a result low bit rates are generated. The method employed in RS interpolation is to first classify the low-resolution source data; once this has been done, interpolation is performed using a filter which is optimal for the selected class. For example, edges are interpolated using filters which do not smooth out their sharp transitions.

2.2 Limits on super-resolution and how to break them

Nearly all super-resolution algorithms are based on the fundamental constraints that the super-resolution image should generate the low resolution input images when appropriately warped and down-sampled to model the image formation process. (These reconstruction constraints are normally combined with some form of smoothness prior to regularize their solution.) In the first part of this paper, we derive a sequence of analytical results which show that the reconstruction constraints provide less and less useful information as the magnification factor increases. We also validate these results empirically and show that for large enough magnification factors any smoothness prior leads to overly smooth results with very little high-frequency content (however many low resolution input images are used.) In the second part of this paper, we propose a super-resolution algorithm that uses a different kind of constraint, in addition to the reconstruction constraints. The algorithm attempts to recognize local features in the low resolution images and then enhances their resolution in an appropriate manner. We call such a super-resolution algorithm a *hallucination* or *reconstruction* algorithm[11]. We tried our hallucination algorithm on two different datasets, frontal images of faces and printed Roman text. We obtained significantly better results than existing reconstruction-based algorithms, both qualitatively and in terms of RMS pixel error.

Super-resolution is the process of combining multiple low resolution images to form a higher resolution one. Numerous super-resolution algorithms have been proposed in the literature [12] [13]. If there is relative motion between the camera and the scene, then the first step to super-resolution is to register or align the images; i.e. compute the motion of pixels from one image to the others. The motion fields are typically assumed to take a simple parametric form. The second, fusion step is usually based on the constraints that the super-resolution image, when appropriately warped and down-sampled to take into accounts the alignment and to model the image formation process, should yield the low resolution input images. T

2.3 Sparse Bayesian learning and the relevance vector machine

Relevance Vector Machines(RVM)[14] have been fashioned from a sparse Bayesian learning(SBL)framework to perform supervised learning using a weight prior that encourages sparsity of representation. This proposed method introduces a general Bayesian framework for obtaining sparse solutions to regression and classification tasks utilizing models linear in the parameters. Although this framework is fully general, we illustrate our approach with a particular specialization that we denote the 'relevance vector machine' (RVM), a model of identical functional form to the popular and state-of-the-art 'support vector machine' (SVM).It makes use of basic functions since the number of support vectors grows linearly with the size of the training set. We demonstrate that by exploiting a probabilistic Bayesian learning framework, we can derive accurate prediction models which typically utilise dramatically fewer basis functions than a comparable SVM while offering a number of additional advantages. These include the benefits of probabilistic predictions, automatic estimation of 'nuisance' parameters, and the facility to utilise arbitrary basis functions (e.g. non-'Mercer' kernels). We detail the Bayesian framework and associated learning algorithm for the RVM, and give some illustrative examples of its application along with some comparative benchmarks. We offer some explanation for the exceptional degree of sparsity obtained, and discuss and demonstrate some of the advantageous features, and potential extensions, of Bayesian relevance learning.

2.4 Empirical filter estimation for sub pixel interpolation and matching

It maximizes the real performance on training images not on the design of theoretical criteria. Empirical filter estimation uses sub pixel correlation for matching and resampling. Rather than using traditional frequency space filtering theory or ad-hoc interpolators such as sp- lines, we take an empirical approach finding optimal sub pixel interpolation filters by direct numerical optimization Sub pixel image is projecting the pixel intensities for low level problem. This is done for deforming the image. Critical impact of sub pixel matches the image interaction. Instead of using the frequency-space filtering theory the empirical approach is followed for finding the optimal filters. Training set consists of larger images with different translations that impersonate the spatial functions of real pixels. The realistic results provides the different parametric forms under conventional and prediction of the robust metrics. The outcome of computing ("jaggies") study the achievement of resulting filters. The sub pixels are obtained. The Methods are:

1 Direct minimization of filter interpolation error on real training images various window sizes and filter types (separable, non-separable, and symmetric)
2 large optimization problems
3 Limited Memory Quasi-Newton methods.
4 Generate training data by sub sampling large images at sub pixel shifts
5 exploit scale-invariance & edge-dominated high-freq. spectra of natural images
6 to mimic real zooms, subsample using a realistic Pixel Response Function (PRF)

The theory does not ensure that the deletion of an h-component of an image will effectively change the image Proposition. The corollary of this observation is that deleted h-components of an image may reappear in the result. As the h-component is just a representation of the decomposition of the image according to a particular h-connection, its properties are thus inherited from the chosen h-connection, and they cannot be specified until such an h-connection has been chosen. These theoretical developments are illustrated by their application on a fuzzy h-connection recently. Existing approach allows us to represent the different fuzzy h-connected components of an image in a single tree structure. This provides a convenient representation to design fuzzy h-connected operators and to reuse all existing algorithms imagined for the connected component tree in this new context.

2.5 EDGE BASED METHOD:

Edge-based methods mainly consider the local information around contours, such as the grey level gradient. Kass[16] propose the snake model which is the best known edge-based active contour method. Caselles[17] propose a geodesic model which reflects more intrinsic geometric image measures than the snake, using the prior knowledge that the larger the gradient at a pixel, the higher the probability that the pixel belongs to an object's edge. Paragios and Deriche[18][19] improve the geodesic model in using level sets to describe contours and using a gradient descent algorithm to optimize contours. The merits of edge-based methods are their simplicity, intuitiveness, and effectiveness for determining contours with salient gradient.

They have the following limitations: a) They only consider the local information near to a contour, and thus the initial contour must be near to the object. b) Contour sections lying in homogeneous regions of an image cannot be optimized. c) They are of course sensitive to image noise.

2.6 REGION BASED METHODS

Region based methods usually divide an image into object and background regions using statistical quantities, such as mean, variance, or histograms of the pixel values in each region. Chan and Vese approximate an image by a mean image with regions whose boundaries are treated as object edges. Zhu and Yuille present a statistical and variational framework for image segmentation using a region competition algorithm. Yilmaz *adopt* the features of both object and background regions in the level set evolution model. Mansouri[20] proposes an algorithm for formulating contour tracking as a Bayesian estimation problem.

For the region-based methods, prior knowledge of object color and texture may be incorporated into the contour evolution process. Color prior knowledge is usually represented using object appearance models such as color histograms, kernel density estimation, or Gaussian mixture models (GMMs). For example, Yilmaz *et al* use kernel density estimation to model color features for estimating contours. Bibby and Reid use color histograms to model appearances and perform contour-based tracking at frame rates. Region texture features are usually modeled using the Gabor filer, the co-occurrence matrix, or Markov random fields (MRF), etc. For example, Sagiv *et al.* use Gabor features to perform textured image segmentation. Pons *et al.[22]* an active contour using texture features which are extracted using unsupervised learning. Yilmaz *et al.* use the Gabor filter to model region texture features for determining contours.

The merit of the region-based methods is that regions' statistical information, together with the prior knowledge of object color and texture, can increase the robustness and accuracy of contour evolution. The limitation of the current region based methods is that the pixel values are treated as if they were independent for the posterior probability estimation. This independence assumption makes the obtained contour sensitive to disturbances caused by similarities of color or texture between the object and the background.

2.7 SHAPE PRIOR-BASED METHODS

Shape prior-based methods statistically model object shape priors which are used to recover disturbed, occluded, or blurred contour sections. Leventon *et al.* project orthogonally a set of aligned training shape samples represented by the signed distance maps into a subspace using Principal Component Analysis (PCA). Paragios and Rousson construct a pixel-wise shape model in which local shape variability can be accounted for. Cootes *et al.* propose an active shape model for the different aspects of rigid objects in a shape prior formulation.

Fussenegger propose an online active shape model to perform region segmentation. The incremental PCA algorithm in is used to update the active shape model. Cremers proposes a linear dynamical shape model based on an autoregressive model for tracking a person with periodic motions using level sets. Yilmaz propose a statistical method to learn object shape models which are used to recover occluded sections of a contour. Rathi combine the particle filter with level set evolution. Occlusion is dealt with by incorporating shape information into the weights of the particles. Raviv utilize the symmetry of rigid object shapes to deal with partial occlusions.

The merit of the shape prior-based methods is that the disturbed, occluded, or blurred edges can be recovered. However, the current adaptive shape-based methods may distort undisturbed contour sections which can be found accurately using color features alone, while they globally recover the disturbed contour sections. In real world applications it is necessary to update the active shape model continuously in order to adapt to shape changes. However, the current method for updating the shape model does not simultaneously handle the multiple new shape samples, and fails to compute the sample basis with sample mean updating. The previous dynamical shape model in for periodic motions of non-rigid objects is a simple data fitting process with no high level understanding of shape changes. The model assumes that the underlying motion is closely approximated by a periodic motion, however human motion is rarely exactly periodic.

3 PROPOSED DESIGN

This proposed model for face image normalization for images taken from ORL database with the unity of map contrast and canny map edge. The texture is further divided based on the threshold value and it is configured and detected with the edge pixels. Binarized face image is undergoes the normalization process to improve the quality using H-connection technique.

3.1 HISTOGRAM NORMALIZATION

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

Histogram equalization often produces unrealistic effects in photographs, however it is very useful for face recognition images like faces, smile or skeleton images, often the same class of images that user would apply false-color to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images.

With the color bleaching transform method a gray scale or brighter image is produced from the original color image. Except the white color the original background colors are represented in to a color. Other colors are darker when evaluating original background colors. One drawback is they are dark close to the background. The problem has been overcome by increasing the contrast of the image. Histogram normalization algorithm is applied to gray scale images. Small values in terms of percent are applied to the both ends of gray spectrum(black, white).The pixel values are calculated for gray scale images range from 0 to 255.As a result image has a variance improvement.

3.2 H-CONNECTION MAP

This proposed system is to addresses two major issues of this theory. First, It propose a new axiomatic that ensures that every h-connection generates decompositions that are consistent for image processing and, more precisely, for the design of h-connected filters. Second, reduces the number of extra-spatial noises form the graphed images. The experiment applied to a particular h-connection, and we test this new framework on several classical applications in image processing, i.e., segmentation, connected filtering, and image binarization with PSNR ,FAR factors shown in the **ORL Database** samples images.

Fig. 1. ORL database images

Volume : 3 | Issue : 10 | October 2014 • ISSN No 2277 - 8179

The experiments confirm the suitability of the proposed approach: It is robust to noise, and it provides an efficient framework to design selective filters. This system is highly designed to general method to obtain a hierarchical representation of the decomposition in the h-components, which has proven to be efficient and intuitive for the creation of attribute filters or for detection tasks. This representation is based on the notion of z-zones defined by an equivalence relation on the sup-generating family of the lattice, all points of the z-zone being assigned to the same group of h-components and improves the quality of the image.

We now consider lattice *I* of functions from a discrete domain *E* to interval [0,1] (which is a complete chain).We assume that is equipped with primary set connection *C*. We define the connectivity measure C_f, of image **f** for all x,y € *E.*

$$C_f(x,y) = \max_{M \in P_{x,y}} \min_{p \in M} f(p)$$

With P (x,y)={M € C_x € M,y, € M}, which is the set of all connected sets containing x and y.This can be equivalently defined in terms of graph connectivity by the set of all paths from x to y. If P (x,y) is empty, we set C_f(x,y)=0 , meaning that x and y are not connected.

Algorithm to form histogram h-connection tree of C_f in face image graph to improve features of the image quality.

Input: the original image im,the max-tree of im,

and the parameter of the h-connection

output :the h-component tree of $c^{+}_{f,}$

```
for all nodes n from root to leaves do
    /*   simplify tree                          */
    while n has exactly one child do
        node c = n.child(1);
        n.level = c.level;
        dekete note c;
    if(n is not the root AND
    n-parent.level> n.peaklevel)then
    /* Local maximum is too small        */
    delete branch of node n;
  else
    n.level =min(n.level+ 1 -,n.peaklevel);
    /*  update point lists                  */
    for all nodes n form root to leaves do
        while n has exactly one child do
            node c = n.child(1);
             n.level = c.level;
                delete node c;
        correctpointList(im,n);
```

One can notice that if primary set connection is invariant to translations, rotations, and homothetic transformations (such as the four- or eight-connected neighborhood), then, the fuzzy h-connection built over this set connection is also invariant to these transformations, as is the fuzzy h-component tree.

Nevertheless, the h-connection is only invariant to gray-level value translations of the image apart for the special case of: It is then invariant to any increasing gray-level transformation. Then, the method to compute an h-component can be adapted to build the complete h-component tree. The proposed procedure is composed of both algorithms 1 and 2. The pseudocode assumes that each node is equipped with two attributes,i.e., the level and the peak level (highest level in its branch), and a function child(n) that returns the child. The first algorithm increases the level of each node and deletes useless branches (branches that do not have sufficient contrast to generate an h-component). Procedure delete node deletes the given node and gives all its children to its father, whereas procedure delete branch deletes the given node and all its children.

At the end of the algorithm, all attributes can be correctly computed according to the h-connection. The second algorithm aims at restoring the good point list to all nodes according to their new levels. It uses a stack structure (with traditional push and pop operators) to explore the branch up to the needed level.

While the Max-Tree computation over an image of 1 million pixels in double precision takes 14 s with max tree algorithm for 481 384 nodes, the transformation into the h-component tree takes 5 s for 3113 nodes in the result (code written in matlab and executed on a 2.66-GHz processor).

4. RESULTS AND DISCUSSIONS

The primary set connection results are invariant to translations, rotations, and homothetic transformations (such as the four- or eight-connected neighborhood), then, the fuzzy h-connection built over this set connection is also invariant to these transformations, as is the fuzzy h-component tree. Nevertheless, the h-connection is only invariant to gray-level value translations of the image apart for the special case of undergone histogram cut process that was shown in the input figures(c,d).

Then, the method to compute an h-component can be adapted to build the complete h-component tree. The proposed procedure is composed of both algorithms 1 and 2. The pseudocode assumes that each node is equipped with two attributes, i.e., the level and the peak level (highest level in its branch), and a function *child(n)* that returns the child. The first algorithm increases the level of each node and deletes useless branches (branches that do not have sufficient contrast to generate an h-component). Procedure *delete node* deletes the given node and gives all its children to its father, whereas procedure *delete branch* deletes the given node and all its children as shown in the input image.

Fig.(a,b) as input image from ORL Database

From the given input image, the H-connection normalization process for the pattern training of face recognition.

(c)

(d)

Fig.(c,d) shows the segmentation of faces texture from background layer

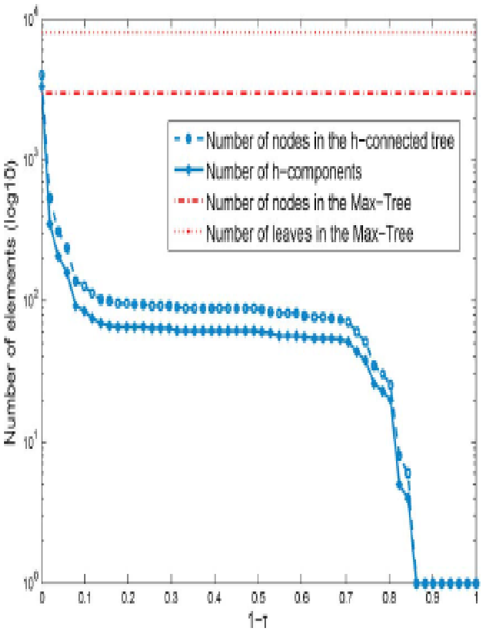
(e)

(f)

Fig. (e, f) shows the normalization of H-coordinates per pixel rate of given images from ORL Database

Fig. c,d,e,f shows the h-connection results using H-Connection map with enhanced feature in the image

At the end of the algorithm, all attributes can be correctly computed according to the h-connection normalization process. The second algorithm aims at restoring the good point list to all nodes according to their new levels. It uses a stack structure (with traditional push and pop operators) to explore the branch up to the needed level. While the Max-Tree computation over an face recognition image of 1 million pixels in double precision takes 14 s with Najman and Couprie's algorithm 384 nodes, the transformation into the h-component tree takes 5 s for 3113 nodes in the result (code written in matlab and executed on a 2.66-GHz processor).



Graph shows the h connection elements feature improvement in the given input images from ORL Database

Moreover, according to these algorithms, it is clear that any pruning of the h-component tree of the h-connection performed according to an increasing criterion, followed by an h-reconstruction will produce an idempotent, increasing, and anti extensive morphological operator, i.e., a morphological opening.

The test consists in performing an area filter (area greater than 30 pixels) using the proposed h-component tree, compared with a traditional vectorial area filter with a Max-Tree. The tests using the Max-Tree were performed twice, i.e., the first time using the same area limit as with the h-component tree (30 pixels) and the second time using a smaller area limit (10 pixels) as nodes in the h-component tree tend to be larger than in the Max-Tree. The experiment shows that our approach is very accurate in extracting small features that have sufficient contrast from a larger object. The background is hardly affected, and more importantly, the morphology of the galaxy is not affected (the very bright central zone is not cut, and morphological details in the arms are preserved). On the contrary, the Max-Tree modifies the background and the fine structures of the galaxy.

CONCLUSION

This experiment measures the performances of this proposed normalization technique over the whole DIBCO benchmarking data set. The data set is composed of thousands of images and images particularly from the **ORL** database. The ground truth of the data set is composed of manual segmentations of the images given by the authors. First the contrast is improved with a linear histogram cut (saturation of the 2% brightest pixels), and the edges of the image are detected using a simple operator, together with an Otsu thresholding[23]. Then, the local threshold value relies on the values of edge pixels in a window of 32 pixels, If there is less than 10 edge pixels in the window, their mean value is used; otherwise, the threshold is set to the first quartile of the edge values. Finally, the result is enhanced using a binary closing by reconstruction of the image by a circular structuring element with a 5-pixel diameter. The result shows the result of the binarization of h-connection with substantial feature improved on two images of the benchmarking data set. Based on the **ORL** database images the normalized technique is proposed. This technique provides face segmentation, normalization and confidentiality.

FUTURE ENHANCEMENT

The future of hyper connection of pixels residual transformed high rate of face recognition images into grayscale images by computing the mean of the RGB channels and estimated the histogram on doing the region based segmentation process. The performances are evaluated in terms of F-Measure and peak signal-to-noise ratio (PSNR), which are the two highlighted measures (among four) involved in the conventional image processing, It seems clear that large groups of h-connections must exist, which share similar properties of their invariance, i.e., the behavior of their z-zones (do they fulfill the requirements of proposition) according to the image resolution.

REFERENCE

[1] J. Serra, Image Analysis and Mathematical Morphology. II: Theoretical Advances. London, U.K.: Academic Press, 1988. | [2] H. Heijmans, "Connected morphological operators for binary images," Comput. Vis. Image Understand., vol. 73, no. 1, pp. 99–120, Jan. 1999. | [3] J. Serra and P. Salembier, "Connected operators and pyramids," in Image Algebra and Morphological Image Processing IV, E. R. Dougherty, P. D. Gader, and J. C. Serra, Eds. Bellingham, WA: SPIE, 1993, pp. 65–76. | | [4] P. Salembier and J. Serra, "Flat zones filtering, connected operators, and filters by reconstruction," IEEE Trans. Image Process., vol. 4, no. 8, pp. 1153–1160, Aug. 1995. | [5] P. Salembier, A. Oliveras, and L. Garrido, "Anti-extensive connected operators for image and sequence processing," IEEE Trans. Image Process., vol. 7, no. 4, pp. 555–570, Apr. 1998. | [6]. J. J. Eggers, J. K. Su, and B. Girod, "Public key normalized by eigenvectors of linear transforms," in Proc. Eur. Signal Processing Conf:, Tampere, Finland, Sept. 2000. | | [7]. Coatrieux G, Lecornu L " A review of image normalized applications in healthcare".Proceedings of the 28th Annual International Conference of the IEEE: Engineering in Medicine and Biology Society,EMBS ,2006. | [8]. Memon N. Normalized of medical images for content authentication and copyright protection. PhD thesis, Pakistan: Faculty of Computer Science and Engineering, GIK Institute of Engineering Sciences and Technology; May 2010. | [9]. Zain J M, Baldwin L P, Clarke M 2009 Reversible normalized for authentication of DICOM images.Proc. 26th Annu. Int. Conf. Eng. Med. Biol. Soc. (EMBC 2004) 2: 3237–3240. | [10]. P. Wong, "A Public Key Watermark for Image Verification and Authentication,"Proceedings of ICIP'98, pp. 425-429, 1998. | [11]. Zhou X Q, Huang H K 2001 Authenticity and integrity of digital mammography images. IEEE Trans. Med.Imag. 20(no. 8): 784–791. | [12]. B. Mathon, "Development of safe normalized methods for tracing of multimedia contents", International thesis cotutelle, University of Grenoble and of Louvain, (2011). | [13]. C.S. Woo, J. Du, and B. Pham, Multiple watermark method for privacy control and tamper detection in medical images, WDIC2005 pages, Australia,February, (2005), pp. 59–64. | 14]. L.O.M. Kobayashi, S.S. Furuie, and P.S.L.M. Barreto, Providing Integrity and Authenticity in DICOM Images: A Novel Approach, IEEE Trans Inform Technol Biomed, 13 (2009).. | | [15]. F. Hartung and B. Girod, "Fast public-key normalized of compressed video," In Proc. Of the IEEE Intl. Conf on Image Processing 1997, vol. 1, pp. 528-531, October 1997. | | [16].H. M. Chao, C.M. Hsu, S.G. Miaou, "A Data Hiding Technique With authentication,Integration, and Con_dentiality for Electronic Patient Records", IEEE Transactions on Information Technology in Bio-medicine, Vol. 6, No. 1, pp. 46-53, March 2002. | [17]. S. G. Miaou, C. M. Hsu, Y. S. Tsai, H. M. Chao, "A Secure Data Hiding Technique with Heterogenous Data Combining Capability for Electronic Patient Records",Proceedings of IEEE International Conference in Medicine and Biology Society (EMBC'00), Chicago, USA, Vol. 1, pp. 280-283, 2000. | [18]. A. Kannammal, S. Subha Rani, K. Pavithra, Authentication of DICOM medical images using independent component analysis (ICA), Int J Med Eng Inform 4 (2012). ||[19]. Dariusz Bogumi," An asymmetric image normalized scheme resistant against geometrical distortions" 2005 Elsevier B.V. | 20. B.Nassir, R.Latif, A.Toumanari," Secure transmission of medical images by normalized technique"IEEE 2012. | 21. M. Kutter, "Digital ImageNormalized : Hiding Information in Images", PhD thesis, | University of Rhode Island, Kingston, USA, 1999. | [22]. C.-T. Hsu, J.-L. Wu, "Hidden Digital Wateramrks in Images", IEEE Transactions on Image Processing, Vol. 8, pp. 58-68, 1999. | [23]. G.-J. Yu, "Digital Image Normalized for Copyright Protection and Authentication", PhD Thesis, National Central University, Taiwan, R.O.C, 2001. | [24] J. Lim, D. Ross, R. S. Lin, and M. H. Yang, "Incremental learning for visual tracking," in Advances in Neural Information Processing Systems. Cambridge, MA: MIT Press, 2004, pp. 793–800. | | [25] Y. Li, "On incremental and robust subspace learning," Pattern Recognit., vol. 37, no. 7, pp. 1509–1518, 2004. | [26] N. Paragios, M. Rousson, and V. Ramesh, "Matching distance functions: A shape-to-area variational approach for global-to-local registration," in Proc. Eur. Conf. Comput. Vis., 2002, pp. 775–789. |