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Comparative Study of Image Restoration Using Fusion Technique

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ABSTRACT: In Image fusion technique we combines information from various images of the same picture to get a composite image which is suitable for further image processing tasks, and also enhancing the perception of a scene. In this paper a comparative study of two techniques Multilevel Depth and Image Fusion for Human Activity Detection, and Multi scale Image Fusion Using the Un-decimated Wavelet Transform with Spectral Factorization and Non orthogonal Filter Banks. In first method on two activity recognition benchmarks (one with depth information) and a challenging gray scale + depth human activity database that contains complex interactions between human–human, human– object, and human–surroundings demonstrate the effectiveness of the multilevel gray scale + depth fusion scheme. Higher recognition and localization accuracies are obtained. The other un-decimated wavelet transform (UWT)- based fusion scheme is used. Which splits the image decomposition process into two successive filtering operations using spectral factorization of the analysis filters? The actual fusion takes place after convolution with the first filter pair. The non sub sampled nature of the UWT allows the design of non orthogonal filter banks, which are more robust to artefacts introduced during fusion additionally improving the obtained results.

KEYWORDS: Energy efficient algorithm; Manets; total transmission energy; maximum number of hops; network lifetime

I. Introduction

There is lots of research on image fusion some is refer here Gonzalo Pajares et al. [1] Proposed wavelet decomposition, i.e. a multi resolution image fusion approach. The images with same or different resolution levels, may include range sensing, visual CCD, infrared, thermal or medical. Chien et al. [2] solved the gamut problem without appealing to color clipping. The iNIHS space includes two halves, one being constructed from the lower half of the RGB cube by RGB to IHS transformations, and the other from the upper half of the RGB cube by CMY to HIS transformations. While incurring no out-of-gamut colors, desired intensity substitutions and additions in substitutive and additive image fusions, respectively, are all achievable. Kang et al. [3] proposed extraction method based on image fusion and recursive filtering (IFRF). First, the hyperspectral image is partitioned into multiple subsets of adjacent hyperspectral bands. Then, the bands in each subset are fused together by averaging, which is one of the simplest image fusion methods.[3] Huang et al. [4] proposed an information-based approach for assessing the fused image quality by the use of a set of primitive indices which can be calculated automatically without a requirement for training samples or machine learning. Wang et al. [5] proposed a method, which uses SSC characteristics and local optimization strategy to simulate a low-resolution panchromatic image, can effectively reduce the spectral distortion of the fused image. Huang et al. [6] Proposed spatial and spectral fusion model (SASFM) that uses sparse matrix factorization to fuse remote sensing imagery with different spatial and spectral properties. In the first stage, the model learns from the LSaR data a spectral dictionary containing pure signatures, and in the second stage, the desired HSaR and HSeR data are predicted using the learned spectral dictionary and the known HSaR data. Lee et al. [7] Propose a framework for motion compensated frame rate up conversion (FRUC) based on variation image fusion. The algorithm consists of two steps: 1) generation of multiple intermediate interpolated frames and 2) fusion of those intermediate frames. In the first step, determine four different sets of the motion vector field using four neighbouring frames. Then generate intermediate interpolated frames corresponding to the determined four sets of the motion vector field, respectively. Ni et al. [8] proposed a complex activity recognition and localization framework that effectively fuses information from both greyscale and depth image channels at multiple levels of the video processing pipeline. Byun et al. [9] proposed an

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area-based image fusion algorithm to merge SAR (Synthetic Aperture Radar) and optical images. An integrated image based on these two images is generated by the area-based fusion scheme, which imposes different fusion rules for each segmented area. Finally, this image is fused into a multispectral (MS) image through the hybrid pan sharpening method proposed in previous research. Montagna et al. [10] proposed the inerrability of the obtained field can be improved dramatically through a simple de saturation of the color image (as in the HSV color space). Here it is shown that small changes of the saturation in the linear image space can result in large improvements in the integrability of tensor gradients calculated in logarithmic color space. This result is important for two reasons. 1) Log-differences are more perceptually meaningful. 2) In log-space we can operate with retinex algorithms, which are well known techniques for contrast enhancement. Bhatnagar [11] proposed fusion framework multimodal medical images based on non-subsampled contourlet transform (NSCT).The source medical images are first transformed by NSCT followed by combining low- and high-frequency components. Two different fusion rules based on phase congruency and directive contrast are proposed and used to fuse low- and high-frequency coefficients. Finally, the fused image is constructed by the inverse NSCT with all composite coefficients. Li [12] proposed a remote sensing image fusion method with sparse representations over learned dictionaries. Li. et al. [13] proposed a method based on a two-scale decomposition of an image into a base layer containing large scale variations in intensity, and a detail layer capturing small scale details. A guided filteringbased weighted average technique is proposed to make full use of spatial. Miles et al. [14] proposed CT/MR spine image fusion algorithm based on graph cuts. This algorithm allows physicians to visually assess corresponding soft tissue and bony detail on a single image eliminating mental alignment and correlation needed when both CT and MR images are required for diagnosis. Pertuz et al. [15] proposed a algorithm for computing the all-in-focus image from a sequence of images captured with a low depth-of-field camera is presented. The proposed approach adaptively fuses the different frames of the focus sequence in order to reduce noise while preserving image features

II. METHODOLOGY OF MULTILEVEL DEPTH AND IMAGE FUSION FOR HUMAN ACTIVITY DETECTION

A. MOTIVATION

Our approach is motivated by the observation that depth information can be well utilized to enhance the quality of representations in three stages of the action recognition pipeline including: 1) human centric action features (i.e., key poses); 2) human-to-human (object) interaction contextual features; and 3) global scene contextual features. These stages of feature representations have been widely used in the action recognition literature; however, previous works only utilize 2-D images/videos to obtain these features and often result in imperfect representations since real actions occur in 3-D. Therefore, our contribution is to enhance the feature extraction and representation in all three stages by using depth images. In particular, depth information is utilized to:

1) improve the accuracy of human key pose detection since the depth image provides good foreground/background segmentation cues; 2) measure human-to-human (object) interaction contexts including relative distance, velocity, and temporal ordering directly in 3-D, as this can remove the measurement ambiguity by using 2-D images only; 3) directly measure the 3-D scene structure, as it helps to improve the action recognition accuracy for these scene dependent actions

B. OVERVIEW OF THE MULTILEVEL DEPTH AND IMAGE FUSION SCHEME

The basic idea is to integrate the depth information into multilevel processing pipeline for detecting human activities that involve human/human, human/object, or human/surrounding interactions. Fig. 1 illustrates our proposed processing pipeline for activity recognition and localization.

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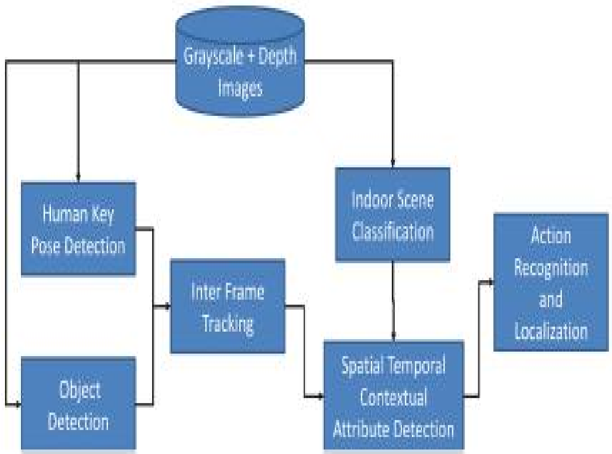

Fig.1.Overview of the proposed action detection framework In the third stage, depth information is utilized for classifying the indoor scenes into different scene categories. Finally, the obtained spatial–temporal interaction attributes, key pose attributes of the track lets and the scene classification results are integrated by a latent structural SVM for discriminatively recognizing and localizing activities.

Depth information at various processing stages is utilized and integrated in the following way. In the visual feature extraction step, here detected human key pose and object of interest in every input frame of the gray scale image sequence and the corresponding depth maps provide further constraints to filter out false detections. These human key pose and object detections are afterward spatially and temporally matched throughout frames into track lets by applying the motion constraints in both gray scale and depth channel.

The invalid detections without sufficient temporal durations are further filtered out at this stage. In the next stage, of model the 3-D spatiotemporal interaction/contextual attributes using combined gray scale and depth information. In the third stage, depth information is utilized for classifying the indoor scenes into different scene categories. Finally, the obtained spatial–temporal interaction attributes, key pose attributes of the track lets and the scene classification results are integrated by a latent structural SVM for discriminatively recognizing and localizing activities

C. DEPTH CONSTRAINED HUMAN/OBJECT DETECTION AND TRACKING

The first step in action recognition is to extract meaningful and representative visual features to measure the motion, Shape, pose, etc., of the human subject(s) performing a certain activity. Although there exist various complex representations of human actions, human can easily recognize what a person is doing even by looking at a single frame without examining the whole sequence. in this paper, human key pose as a primitive representation for human actions. The advantages of this representation are as follows: 1) key pose based representation is more compact and therefore it reduces the computational complexity; and 2) it is robust to variations in execution styles of the same action.

D. 3-D SPATIAL–TEMPORAL CONTEXTUAL ENCODING

Conventional 2-D images, therefore, the contextual information such as relative distance, relative speed, etc., can only be measured in 2-D, and therefore inaccurate measurement and ambiguity exists due to perspective projection. When a depth image is available, spatiotemporal contextual information for interaction can be measured directly in 3-D. Here a set of 3-D spatiotemporal contextual attributes between trackless of human key poses or objects, by explicitly utilizing the combined information from gray scale and depth images.

The advantage of modelling 3-D spatiotemporal contextual interaction attributes between two trackless is obvious. For example, the action discussion between two people requires that two human subjects stand nearby within a relatively fixed distance over a sequence of frames, and their relative speed is approximately zero. However, the actual distance

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between two human subjects inferred from a conventional image could be ambiguous as their displacement in the depth direction is not considered. Using the depth image solves this problem easily.

E. DEPTH-BASED SCENE CLASSIFICATION

Knowing the type of the scene can also benefit action recognition. For example, the action "A person types on a keyboard" usually does not occur in an outside-office scene (e.g., corridor). Similarly, the action "A person unlocks an office and then enters it" always occurs in a scene that contains a door. It is noted that when a depth image is available, it can use the 3-D geometric attributes for modelling the scene type. In particular, it can use the 3-D plane orientations. To model the geometric scene structure, we first transform the depth image into a normal map. The normal map is composed of values of each cell plane's (patch) 3-D normal, which is a normalized vector that indicates the orientation of a plane. 3-D normal's can be directly computed by fitting a plane to 3-D points sampled from a local image patch that are assumed to be planar.

For each pixel in the depth map, use its 7×7 neighbourhood pixels' 3-D coordinates to fit a plane, and compute the plane's normal. After calculating the normals, we project the 3-D plane directions onto the 2-D image plane. Finally, we represent the scene by: 1) the histogram of four major orientations (up, down, left, right), and 2) 2-D coordinates of the centre of gravity of the four projected directions. In this paper, we define 5 types of indoor scenes corresponding to typical scenarios of office environment. More scenes could be added for any new given tasks. An example of plane orientation map is given in Fig. 4.

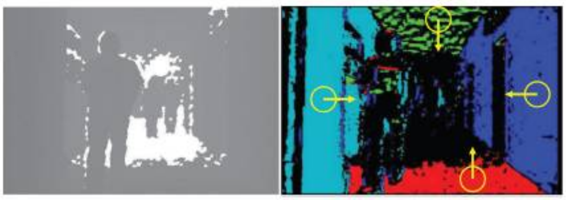

Fig.2. Example scene type (depth image) and its corresponding projected normal map Red, green, blue, and cyan represent up, down, left, and right, respectively

F. LATENT SVM MODEL FOR ACTIVITY DETECTION

We are now able to describe how we model an activity (which contains interactions) in a video sequence, similarly to the previous part-based model for action recognition.

III. UWT-BASED FUSION SCHEME WITH SPECTRAL FACTORIZATION

An input image can be represented in the transform domain by a sequence of detail images at different scales. The orientations with approximation image at the coarsest scale.

A. SPECTRAL FACTORIZATION

Plenty of transforms are at our disposal to perform image fusion tasks, among them the DWT, CVT and CT, as well as the UWT, DTCWT and NSCT. A first classification can be made based on the underlying redundancy and shift-variance of these transforms. Whereas the highly redundant UWT, DTCWT and NSCT are invariant to shifts occurring in the input images, the DWT, CVT and CT represent shift-variant transforms with no or limited redundancy. As stated in various studies (e.g. [1], [13], Motivated by these observations, we will discard the DWT, CVT and CT and focus solely on redundant transforms in our ongoing [19]), redundancy and shift-invariance are desirable properties in image fusion applications since they allow for a higher robustness to rapid changes in coefficient values, thus, reducing the amount of reconstruction errors in the fused image. discussion. Another crucial point in multi scale pixel-level image fusion frameworks is the choice of an appropriate filter bank.

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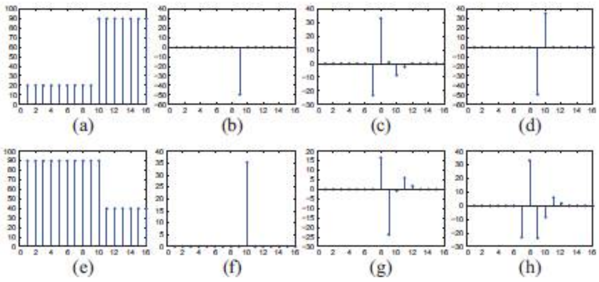

Fig.3. Coefficient spreading effect.(a) and (e)input signal.(b) and (f) haar filtered input signals.(c) and (g) “db3” filtered input signals.(d) fusion of the haar filtered signals.(h) Fusion of the “db3” filtered signals

In this example the high pass portions of two 1-D step functions are fused using one stage of the 2-tap Haar and 6-tap “db3” filters,1 respectively. The high-pass sub bands, obtained by applying the Haar filter, can be seen in Fig. 3(b) and (f), whereas the result using the 6-tap “db3” filter is illustrated in Fig. 3(c) and (g). It can be observed that the “db3” filter needs five coefficients to represent the step change. Thus, although most energy is concentrated in the central coefficient, the remaining four coefficients correspond to regions where no change in the signal value occurred. When attempting to fuse the two “db3” filtered high-pass subbands we are confronted with a problem, namely, to combine the two signals without losing information. This can be observed in Fig. 3(h), where not all non-zero coefficients from Fig. 3(c) and (g) could be incorporated. On the other hand, the Haar filtered signal contains only one non-zero coefficient corresponding exactly to the position of the signal transition. Thus, as illustrated in Fig. 3(d), both non-zero coefficients are transferred to the fused image without any loss of information.
Therefore, it can be concluded that filters with large support size may result in an undesirable spreading of coefficient values which, in case of salient features located very close to each other in both input images, may lead to coefficients with coincident localizations in the transform domain. Since it is difficult to resolve such overlaps, distortions may be introduced during the fusion process, such as ringing artifacts or even loss of information. Although the situation depicted in Fig. 2 may seem at first somewhat artificial, we will see in the next sections that multi sensor images and, among them, especially medical image pairs often exhibit similar properties. Hence, for these images the fusion performance considerably degrades with an increase of the filter size. We can therefore reduce the problem of choosing a proper redundant multi scale transform to its ability to incorporate a filter bank with a sufficiently small support size, thus, minimizing the coefficient spreading problem.

From this point of view, the UWT appears to be an attractive choice, since, due to the standard tensor product construction in 2-D, the UWT offers directionality without increasing the overall length of the implemented filter bank -a property not shared by the NSCT and DTCWT.As for the NSCT, the increased filter lengths are mainly due to the iterated nature of the non sub sampled directional filter bank involved. For a thorough discussion on the construction of directional filter banks). In the case of the DTCWT, as reported in , the increased filter length is due to the half-sample delay condition imposed on the filter banks involved, which results in longer filters than in the real wavelet transform case. Following the remarks stated so far, we are tempted to arrive at the conclusion that the best fusion results for source images derived from different sensor modalities, are obtained by simply applying the UWT in combination with the very short 2-tap Haar filter bank. Indeed, surprisingly good results are achieved using this simple fusion strategy for infrared visible and medical image fusion.

However, the Haar filter bank presents some well-known deficiencies, like the introduction of blocking artifacts when reconstructing an image after manipulation of its wavelet coefficients, which might deteriorate the fusion performance in certain situations. This is mainly due to the lack of regularity exhibited by the Haar wavelet. Here a UWT-based fusion approach proposed that splits the filtering process into two successive filtering operations and performs the actual fusion after convolving the input signal with the first filter pair, exhibiting a significantly smaller support size than the original filter. The spectral factorization scheme, as presented in this subsection, cannot be straightforwardly adapted to the NSCT and the DTCWT. This is mainly due to the filter design restrictions imposed by these transforms, preventing the meaningful application of such a factorization scheme. As we are going to show later, the presented

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approach is particularly well suited for the fusion of infrared-visible and medical images, which tend to exhibit a high degree of information at coincident localizations. For these image groups the presented framework outperforms traditional fusion frameworks based on the DTCWT and NSCT

B. FUSION RULE

As for the combination of the input image pairs, a wide range of fusion rules can be found in the literature. In general, these rules vary greatly in terms of their complexity and effectiveness. The spectral factorization method proposed here can be employed together with any fusion rule [25]. Therefore, in order to assess the effectiveness of the proposed method, we applied four different fusion rules. The first investigated combination scheme is the simple "choose max" (CM) or maximum selection fusion rule. By this rule the coefficient yielding the highest energy is directly transferred to the fused decomposed representation

V. RESULTS

Several example frames of the action localization results are given in Fig. 4.We have several observations: 1) for most examples, the activity spatial localization results are precise; 2) different instances of activities have very large scale variations; and 3) multiple activity instances can be detected simultaneously in the same frame.

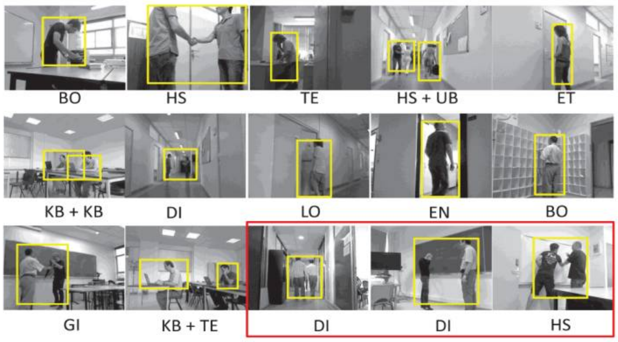

Fig.4.Example frames of the activity recognition and localization results. last three examples highlighted by red bounding box are failure case. We note that the proposed method greatly outperforms the previous art. For the last three examples that are highlighted by red bounding box, the predicted activity class labels are incorrect. This is due to the fact that the current track let-based features cannot well distinguish the cases such as: stand together versus discussion, pass object versus shake hand. In the future, fine grained local motion features should be developed to handle these cases. In addition, we also study the effect of the track let extraction parameter tdist on the final action detection performance.

A. *RESULT ANALYSIS USING FILTER BANKS.*

In this section the performance of the proposed fusion framework will be investigated, using three different sets of Image-pairs. The first set consists solely of infrared-visible image pairs, whereas the second and third group comprises medical and multifocal images, respectively. The corresponding thumbnails of all used source images, divided into their corresponding groups, and are illustrated in Fig. 5. The performance of the proposed UWT fusion scheme with spectral factorization is compared to the results obtained by applying the NSCT, the DTCWT and the UWT without Spectral factorization. Additionally, we will also consider some bi orthogonal filters, which are frequently used in image processing applications such as the LeGall 5/3, CDF 9/7 Rod 6/6 filter bank [17]. In order to avoid referring to filter banks by their respective equation numbers, we will associate the following names to them. Henceforth, the filter as for the objective assessment of multi scale image fusion, a considerable number of evaluation metrics can be found in the literature (see [18-23] for an overview).

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This leads to a better conservation of features which are located close to each other in the input images. In addition, this solution leaves room for further improvements by taking advantage of the non sub sampled nature of the UWT, which permits the design of non-orthogonal filter banks where both synthesis filters exhibit only positive coefficients. Such filters provide a reconstructed, fused image less vulnerable to ringing artifacts. The obtained experimental results have been analyzed in terms of the three objective metrics QAB/F, MI and QP. It is showed that for multi sensor images, such as infrared-visible and medical image pairs, the proposed spectral factorization framework significantly outperforms fusion schemes based on state-of-the-art transforms such as the DTCWT and NSCT, independent of the underlying fusion rule. Among them, non reference fusion scores which evaluate fusion for a large set of different source images without presuming knowledge of a ground truth are of particular interest. These metrics consider only the input images and the fused image to produce a single numerical score that indicates the success of the fusion process.

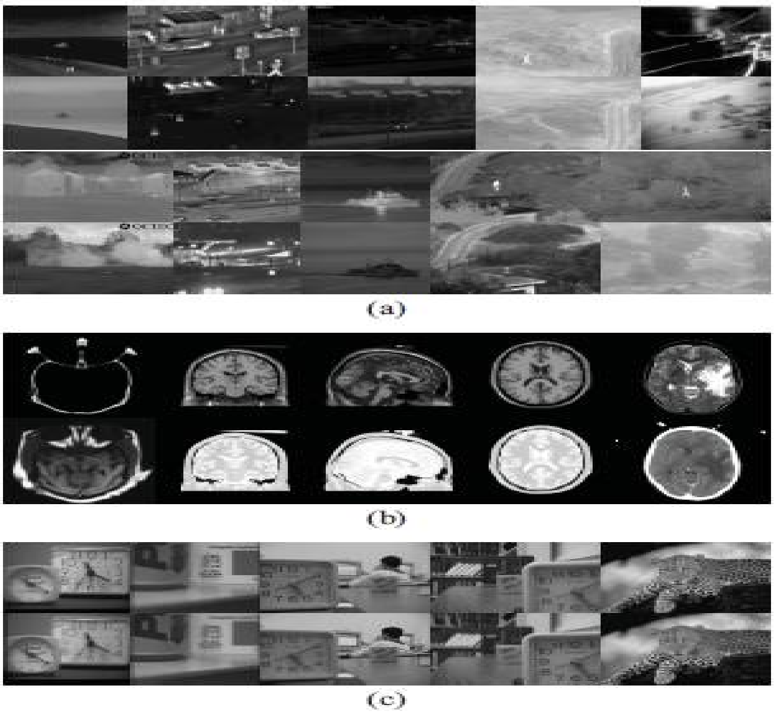

Fig. 5 thumbnails of all image pairs used for evolution purposes.(a) infrared-visible images(ten pairs).Top row : infrared images. Bottom row: visible images.(b)Medical images(five pairs).(c)multifocal images (five pairs).

V. CONCLUSION

Here is multilevel depth information in the video processing pipeline to boost detection accuracy. Experimental results on two activity recognition benchmarks (one with depth information) and a challenging depth + grayscale activity dataset demonstrate the effectiveness of the proposed scheme of fusing depth and grayscale images for robust individual visual feature extraction, accurate 3-D spatial and temporal interaction contextual modeling, and the high-detection accuracy for complex activity and interaction.

In UWT-based pixel-level image fusion approach spectrally divides the analysis filter pair into two factors which are then separately applied to the input image pair, splitting the image decomposition procedure into two successive filter operations and improves fusion results for images exhibiting features at nearby located or coincident pixel locations - conditions commonly but not exclusively found in multi sensor imagery. The actual fusion step takes place after convolution with the first filter pair. It is equivalent, as far as the coefficient spread is concerned, to a filter with significantly smaller support size than the original filter pair. Thus, the effect of the coefficient spreading problem, which tends to considerably complicate the feature selection process, is successfully reduced.

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