Feature Level Fusion of Night Vision Images Based on K-Means Clustering Algorithm

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Abstract: **A region based visual and thermal image fusion technique based on k-means clustering algorithm is presented in this paper. This novel region fusion method segments regions of interest from thermal image using k-means clustering algorithm. Later on, these regions of interests are fused with visible image in DWFT domain. A prominent feature of our proposed technique is its near-real-time computation. Objective comparison of the scheme proposed in this paper has been done with other well known techniques. Experimental results and conclusion outlined in this paper will explain how well the proposed algorithm performs.**

Keywords: Image fusion, discrete wavelet frame transform (DWFT), k-means clustering, Discrete wavelet transform (DWT), Mutual Information (MI).

1. INTRODUCTION

For past many years, there has been an increasing interest of researchers in the area of thermal and visual image fusion, because of its applications in both civilian and military projects. The motivation behind this increasing interest is to get better situation assessment; which can never be obtained from the data acquired from a single sensor, either infra-red or visual.

Due to immense advances in sensor technology, the requirement to monitor our surrounding has been greatly increased. In various military and civilian applications, we need to fuse thermal and visible images into a single image because information from single source is not sufficient to provide a clear perception of the real world. In military applications, for example, night vision sensors are normally used for helicopter navigation and driving. Thermal sensors provide clues on the terrain and surrounding environment by sensing emitted infra-red radiation. These features can be as subtle as the cooling hand and footprints left by a person who has recently passed through the area [2].Visible image on the other hand provides information based on the reflected light. If we, in some way, combine images from both sensors, into a single image in real time, it could be used in helmet mounted display for soldiers and fire fighters, or on a penal mounted in a vehicle, which enable the driver to drive with a clear view even in bad weather conditions. In recent years, many researchers have taken keen interest in the use of thermal and visible images to detect mines [3], mapping and scene understanding [4] for military defence applications. Other civilian application areas of image fusion include medical imaging, search and rescue operation, police surveillance and fire fighting [2].

Image fusion is generally performed at three different levels of information representation; these are pixel level, feature level and decision level [5]. Fusing images at pixel level means to perform integration at a level where the pixels are least processed. Each pixel in the fused image is calculated from pixels in the source images by for-example averaging. Fusion at feature level first requires extraction of features from the source images (through e.g. segmentation); fusion then takes place based on features that match some selection criteria. At symbol level/decision level, the output from the initial object detection and classification using source images is then fed into the fusion algorithm. Every image fusion algorithm is performed at one of these three levels or some combination thereof. Algorithm proposed in this paper is based on feature level fusion, images we tend to fuse are segmented into regions and fused image is captured from the integration of required segments from both the images.

Looking in the literature, we find image fusion techniques which vary from simple pixel averaging to complex methods involving principal component analysis (PCA) [6], pyramid based image fusion [7] and wavelet transform (WT) fusion [8]. All these methods mainly fuse images on pixel level, which results in reduction of contrast and addition of artifacts. We fuse image to accelerate or improve the fusion post-processing tasks like object detection or target recognition. Region fusion helps detection of objects or regions of interest with improved confidence. Piella [9] and Zhang et al. [10] proposed region fusion algorithms in which they integrate images with the help of regions of interest.

In this paper a novel image region fusion algorithm is proposed in which images are transformed using DWFT and images are fused after regions from k-means clustering algorithm are acquired.

The subsequent sections of this paper are organized as follows. Section 2 explains the components of the proposed algorithm. Section 3 explains the method with the help of algorithm and flowchart. Section 4 explains Mutual Information (MI), an objective image fusion quality evaluation measure followed by experimental results and conclusion.

2. INGREDIENTS OF PROPOSED SCHEME

The key constituents of our scheme are discrete wavelet frame and k-means clustering. Below we have discussed some of the prospects regarding these techniques.

A. Why DWFT?

The lack of translation invariance together with rotation invariance is the key drawback of DWT in feature extraction. Due to shift variance the fusion methods using DWT lead to unstable and flickering results. This can be overcome with DWFT by calculating and retaining wavelet coefficients at every possible translation of convolution filters or in other words the redundant transforms. More detail can be found in MATLAB wavelet toolbox, where it is called Stationary Wavelet Transform (SWT).

B. k-mean clustering

T. Sobh (ed.), Innovations and Advanced Techniques in Computer and Information Sciences and Engineering, 73–76.

K-means is a technique for clustering which partitions a group of n data items into k groups and finds a cluster center in each group such that a cost function is minimized [11]. This algorithm is used for clustering because of its stability and extensibility. It's a heuristic approach of clustering under unsupervised environment.

3. Proposed Image Fusion Scheme

It is important to know for the readers that the set of images used in this algorithm are registered images. With registration we find correspondence between images. It is necessary because only after it is ensured that spatial correspondence (information from different sensors can be guaranteed to come from identical points on inspected object) is established, fusion makes sense. For image registration, normally two approaches are used. They are global [15] and local [16] motion estimation. More detail on image registration can be found in [12], [13].

A. Algorithm

1. Take DWFT of both visual and thermal image resulting into their 1 approximation and 3 detail sub-bands. The decomposition level in this case has been set to 1. This is because; this decomposition level gives optimum results.
2. Segment the thermal image into important and sub-important regions using k-means clustering algorithm, resulting into a clustered image where zero represents the unimportant region and one represents important region.
   If we visually analyze the thermal image, it contains grey levels either belonging to upper range of grey levels (e.g. greater then 200) or belonging to lower medium range of grey levels (e.g. less than 140). Exploiting this fact, if we segment these grey levels into two parts (i.e. important and sub-important regions), we can extract significant important details from thermal image which can be further used for fusion.
3. Compute the fused coefficient map using the following relation.

$$F(i,j) = \begin{cases} T(i,j) \longrightarrow if C(i,j) = 1 \\ V(i,j) \longrightarrow if C(i,j) = 0 \end{cases} \qquad (1)$$

   here $F(i,j)$ (fused DWFT coefficients) is equated to $T(i,j)$ (Thermal image DWFT coefficients) if Clustered image ($C(i,j)$) is 1 at index i, j and similarly $F(i,j)$ is equated to $V(i,j)$ (visual image DWFT coefficients) when $C(i,j)$ is 0.
4. Take the inverse discrete wavelet frame transform (IDWFT) of the fused coefficient map and get the fused image.

B. Flowchart

The general framework of the proposed algorithm can be shown with the help of flowchart. Algorithmic steps performed at each major step of algorithm are shown in mathematical form in Fig.1.

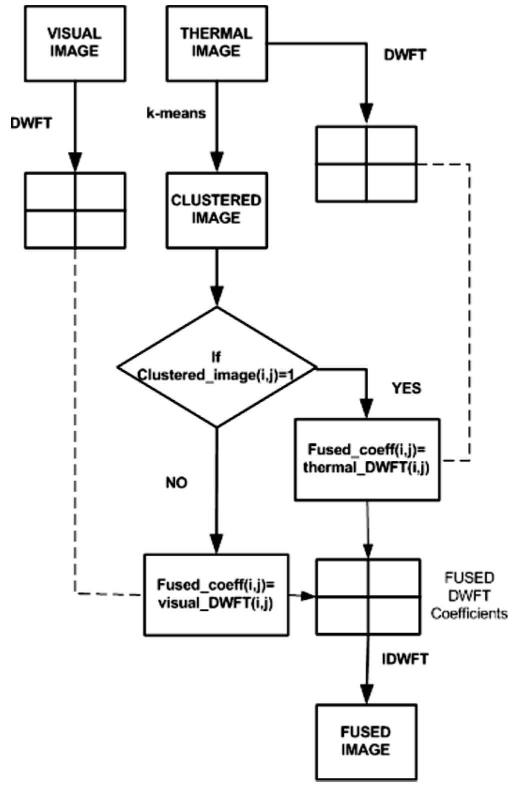

Fig. 1. Flowchart of the proposed scheme

4. Mutual Information

Mutual Information [1] has been used as a objective image fusion quality evaluation measure. Mutual Information of X and Y is the amount of information gained about X when Y is learned and vice versa. It is observed to be zero in case X and Y are independent. Mutual Information between two source images and the fused image is defined as follows.

$$I_{FA}(f,a) = \sum_{f,a} p_{FA}(f,a) \log_2 \frac{p_{FA}(f,a)}{p_F(f)\,p_A(a)} \qquad (2)$$

$$I_{FB}(f,b) = \sum_{f,b} p_{FB}(f,b) \log_2 \frac{p_{FB}(f,b)}{p_F(f)\,p_B(b)} \qquad (3)$$

In equation 2 and 3 $p_{FA}(f,a)$ and $p_{FB}(f,b)$ are the joint histograms of fused image and image A and fused image and image B. The mutual information is thus calculated as:-

$$MI_F^{AB} = I_{FA}(f,a) + I_{FB}(f,b) \qquad (4)$$

The more the value of MI the better is the quality.

5. Results And Discussions

Three existing image fusion schemes are used for comparative analysis of our proposed scheme. These schemes are.