THERMAL-IMAGE QUALITY MEASUREMENTS

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ABSTRACT

Thermal image quality assessment is essential in evaluating the performance of thermal imaging systems. The existing no-reference methods can be roughly categorized using quantification measures as follows: a) Human Visual System measures, b) information measures, and c) image distribution measures. All the above classes of measures are not appropriate for thermal imaging because the structure of thermal images is quite different from visible light images. In thermal images, the temperature of the background is high, temperature difference between objects and the background is small, and it is difficult to determine the link between objective and subjective image quality assessment. There is a need in new thermal image quality measures which can connect objective representation performance and thermal image characteristics. This paper presents new no-reference thermal-imaging measures and elaborates on their applications. They integrate advantages of above-mentioned conventional of measures. Simulation results demonstrate effectiveness of the presented measures in evaluating thermal image qualities in comparison with other well-known assessment tools. Finally, conclusions on more general applicability of these measures are presented.

Index Terms- Thermal Image Enhancemnet, Enhancement Measure

1-INTRODUCTION

Thermal imaging is a non-contact and non-intrusive technique with an advantage of no alteration in the surface temperature and capable of displaying real time temperature distribution. This has been exploited in many industrial and/or research fields where the temperature represents a key variable, including meteorology, environmental studies, medical diagnostics, architecture, etc. [1]. For example, thermal imaging can detect leakage problems in various plants and systems by sensing emissions of thermal energy. Thus such monitoring has the capability to detect and evaluate the presence of any anomalies in thermal distribution profiles. As all objects generate and transfer heat thermal imaging has many advantages compared with traditional temperature measurement methods, including fast response times, wide temperature ranges, fast two dimensional data capture, and high spatial resolution. It is safe, reliable and cost-effective approach for a system inspection and maintenance [2-5].

The structure of thermal images is quite different from the visible light images as it is completely based on the heat distribution of an object. For example, in thermal images, the temperature of the background is high and the temperature difference between objects and the background is small. The quality of a thermal image is usually disturbed by the reduced range of operation of thermal imaging sensors, background radiation and imaging environment. These factors may blur the regions of interest or produce thermal image with low contrast. Therefore, observation and recognition of objects in thermal images is difficult because of inherent thermal characteristic and detector disfigurement etc. [3-7]. Therefore a new measure for thermal imaging assessment should be introduced which exploits both heat characteristic and its relation with existing quality measures for visible light images

In recent years, there has been an increasing interest in developing objective image quality measures. They may be classified into the following categories: (1) full-reference methods, which rely on reference images for evaluating distorted ones; (2) reduced-reference methods, where only partial information about reference images are available; and (3) no-reference approaches, where reference images are not used [8]. Existing measures for color image quality assessment can be classified as: a) Human Visual System (HVS) based [8-16], b) Information Entropy System (IES) based [8,17-19], and c) Distribution-Based System (DBS) based [8,20-21].

To the best of our knowledge, no metric tailored for assessing the quality of thermal images has been introduced so far. In this paper, new quality assessment measures for thermal images are presented based on a new interpretation of image brightness and darkness and their integration with existing image quality measures. The first measure is based on density of local windows assigned on the image and the second measure based on the integration of HVS components and image density of the local windows. The paper is organized as follows: Section 2 introduces the proposed approach. Section 3 presents the experiment results and finally conclusion is expressed in section 4.

2- PROPOSED NEW THERMAL MEASURE OF ENHANCEMENT

In this section new measures on quality assessment of thermal images are presented. The first is based on integration of human visual system and density based measure. The second measure is a combination of features including human visual system, information system and distribution based measure. The uniqueness of presented measures are the following:

a) Image dependent measure based on cross entropy threshold
b) It integrates both intensity and density
c) It adapts to human visual system

Density-based Measure of Thermal-image Enhancement, DMTE: This measure is based on integration of human visual system and a density based measure. Some definitions are required to be introduced as:

Massy Value Definition: Suppose that the image, *I,* is divided to Ω block, $\Omega = k_1 \times k_2$ and it is assumed that the size of ω^{th} block is $k \times l$. Consider the ω^{th} block *(ω=1,..., Ω)* and sorting the density values and intensity of the mentioned blocks we have:

$$P_{min} \leq P_2 \leq P_3 \cdots \leq P_{[T_{k,l}]} \leq \cdots \leq P_{max} \quad (1)$$

$$I_{min} \leq I_2 \leq I_3 \cdots \leq I_{[T_{k,l}]} \leq \cdots \leq I_{max} \quad (2)$$

where $I_i, i = min \cdots max,$ represent of image intensity values of the considered blocks and $P_i, i = min \cdots max,$: stand for mass value which is defined as: $P_j = n_j . j$ is the jth gray level, and $n_j$is the total number of pixels in the image with gray level j..$T_{k,l}$is threshold notation which is determined later. .

Brightness-Darkness Density Definition: The brightness and darkness definitions are defined as:

$$\text{Brightness Density:} P^{\omega}_{B;k,l} = \sum_{[T_{k,l}]+1}^{max} P_i / \sum_{min}^{max} P_i \quad (3)$$

$$\text{Darkness Density:} \; P^{\omega}_{D;k,l} = \sum_{min}^{[T_{k,l}]} P_i \,/\, \sum_{min}^{max} P_i \quad (4)$$

Cross Entropy Brightness-Darkness Definition:$T_{k,l}$ is a threshold which is determined based on minimization of cross entropy between the darkness, $P^{\omega}_{D;k,l}$, and brightness, $P^{\omega}_{B;k,l}$, which means the information theoretic distance between the mentioned components, which is defined as:

$$T_{k,l} = Argmin_{i=min}^{max}\{P^{\omega}_{D;k,l} log \frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}}\} \quad (5)$$

To calculate the threshold an optimization algorithm could be used such as genetic algorithm, recursive algorithm, etc. The Brightness-Darkness Separating algorithm is demonstrated in table 1 as:

Table 1- Brightness-Darkness Separating Algorithm

1-Capturing an input thermal image
2-Appling a color space transform
3-Taking a color channel of the transformed image
4-Decomposing the image into blocks
5-Sorting the mass values within each block, (2)
6-Defining a threshold value for each block
7-Suoppse an initial value for threshold and calculate (3) and (4)
8-Apply an optimization algorithm on (5) to find the threshold

The new thermal metric as a hybrid measure based on human visual system and density-based measures is represented as:

$$DMTE = (\frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} \frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}} \log \frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}}) \quad (6)$$

Density-Intensity Measure of Thermal-image Enhancement: In the proposed measure the integration of both intensity and density of an image is used as the enhancement metric. In fact the new measure is a combination of features include of human visual system, information system and distribution based measure which is defined as:

$$DIMTE = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} (\frac{P^{\omega}_{max;k,l}}{P^{\omega}_{min;k,l}}) \times (\frac{I_{max;k,l}}{I_{min;k,l}})^2 \quad (7)$$

where $P^{\omega}_{max;k,l}$and $P^{\omega}_{min;k,l}$are the maximum and minimum of density value for the specified block respectively. Based on our introduced MEMEE as measure of enhancement [22], the measure proposed in (7) can be modified according to the following definitions:

Brightness-Darkness Intensity Definition: According to the sorted intensity values represented in relation (2), $I^{\omega}_{B;k,l}$ and $I^{\omega}_{D;k,l}$are defined as:

$$\text{Brightness Intensity Component}=I^{\omega}_{B;k,l} = \sum_{[T_{k,l}]+1}^{max} I_i, \quad (8)$$

$$\text{Darkness Intensity Component}= \; I^{\omega}_{D;k,l} = \sum_{min}^{[T_{k,l}]} I_i \quad (9)$$

Therefore the new measure is constructed based on DMTE, DIMTE and MEMEE as:

$$MDIMTE = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} (\frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}})(\frac{I^{\omega}_{D;k,l}}{I^{\omega}_{B;k,l}})^2 \quad (10)$$

The proposed measures are local contrast measure of enhancement. The mentioned measure could also be used as global measurement by applying the concept in whole the image. The measures and their features are summarized in Table 1 and the measurement calculation is illustrated in Fig. 1.

Table 2- Thermal-Image Measurements

Measure	Description	Feature
DMTE	$f = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} \frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}} \log \frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}}$	HVS+DBS
DIMTE	$f = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} (\frac{P^{\omega}_{max;k,l}}{P^{\omega}_{min;k,l}}) \times (\frac{I_{max;k,l}}{I_{min;k,l}})^2$	HVS+IES + DBS
MDIMTE	$f = \frac{1}{k_1 k_2} \sum_{l=1}^{k_2} \sum_{k=1}^{k_1} (\frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}})(\frac{I^{\omega}_{D;k,l}}{I^{\omega}_{B;k,l}})^2$	HVS+IES + DBS

The function "*f*" is called as metric function. It is important that the metric functions no limited to what introduced in the table 2 and could be improved based on other thermal image features and structures.

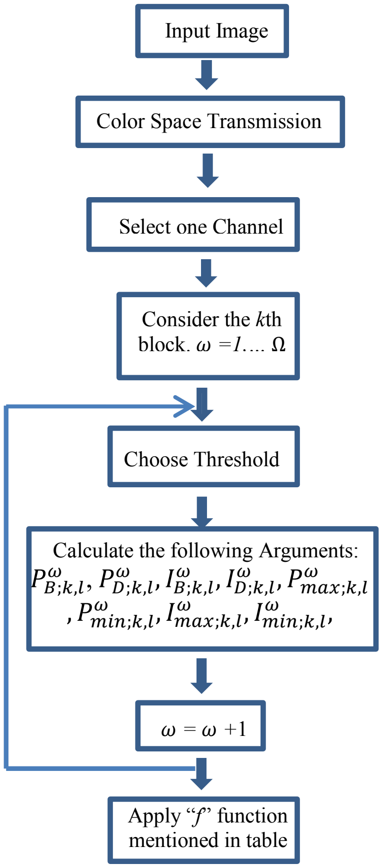


Fig. 1- Thermal Measure System

3- EXPERIMENT

In this section, computer simulation results are presented to evaluate the effectiveness of the new algorithm. The tested images are from [23] and demonstrated in Table.3. The illustrations of the simulation results consist of three types of images. The first is original image; the second is the enhanced image using CLAHE method [24] and the last groups belongs to images enhanced by the introduced algorithms [25]. The database includes 11 thermal image sets. As there are no standard benchmarking datasets for thermal images, therefore for the selected dataset the Mean Score Opinion (MOS) factor is prepared based on a survey at the University of Texas at San Antonio including 30 participants.

MOS is a subjective evaluation method to visually assess the enhanced images by using the mean opinion score represented by ITU-T [26]. The MOS determines which method is most visually pleasing for a human observer. The results of applying the measures based on DMTE and DIMTE are provided in the table 4 and 5 respectively. The average score provided at Table 6 for each measurement algorithm shows that proposed metrics in this article, on average, yields more outperforms than the other measurements.

Table 3- Thermal-Image Database

	Original	CLAHE	Our Method[25]

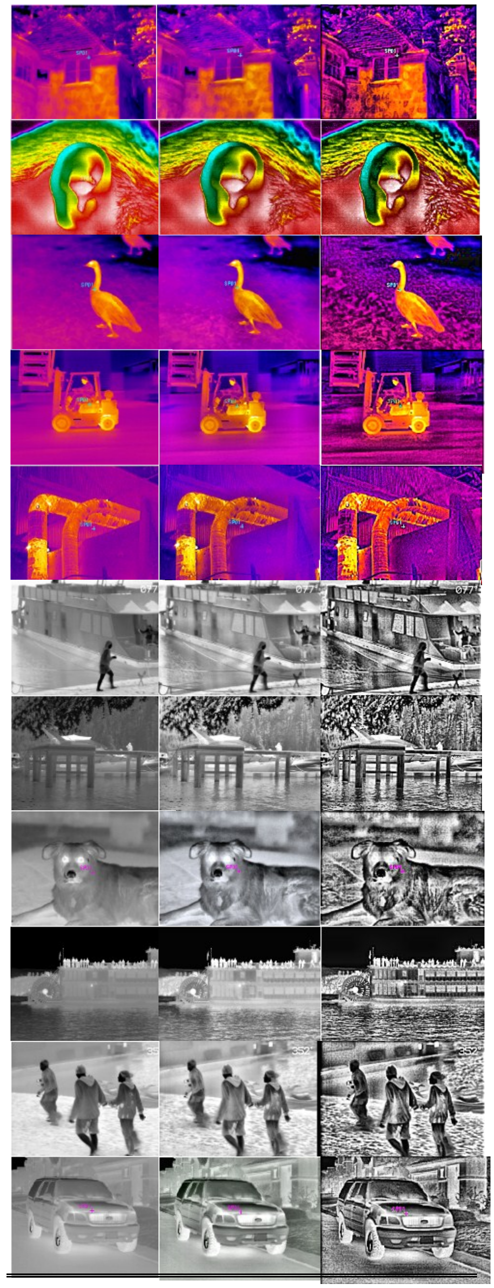


Table 4- Evaluation DIMTE Measure

DIMTE	$\frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\left(\frac{p_{max;k,l}}{p_{min;k,l}}\right)\times\left(\frac{I_{max;k,l}}{I_{min;k,l}}\right)^2$			STD
Set 1-House	1.07	1.11	2.11	0.58
Set 2-Ear	0.23	0.71	1.85	0.83
Set 3-Dock	0.44	0.47	0.74	0.16
Set 4-Lift truck	0.32	0.39	1.02	0.38
Set 5- Pipe	0.24	0.51	1.49	0.65
Set 6-Girl	1.18	1.2	2.21	0.59
Set 7-Boat	1.09	1.15	2.11	0.57
Set 8-Dog	0.24	0.74	1.77	0.78
Set 9-Ship	1.07	1.14	2.08	0.56
Set 10- Beach	1.72	1.87	2.20	0.25
Set 11- Car	0.33	1.14	1.59	0.63

The results of table 4 and 5 show the effectiveness of the new proposed measures to determine different levels of enhancement.

Table 5- Evaluation, DMTE

DMTE V-channel	$\frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}}\log\frac{P^{\omega}_{D;k,l}}{P^{\omega}_{B;k,l}}$			STD
Set 1-House	0.40	0.51	0.79	0.20
Set 2-Ear	0.36	0.59	0.83	0.24
Set 3-Dock	0.09	0.2	0.54	0.23
Set 4-Lift truck	0.19	0.30	0.45	0.13
Set 5- Pipe	0.13	0.34	0.66	0.27
Set 6-Girl	0.53	0.73	0.92	0.19
Set 7-Boat	0.17	0.63	0.89	0.36
Set 8-Dog	0.14	0.65	0.84	0.36
Set 9-Ship	0.09	0.24	0.63	0.27
Set 10- Beach	0.5	0.65	0.84	0.17
Set 11- Car	0.15	0.56	0.7	0.28

Comparison between two measures, DITME and EME, has been depicted in Fig. 2. According to the mentioned results, it seems that DIMTE is better measure for thermal-image enhancement.

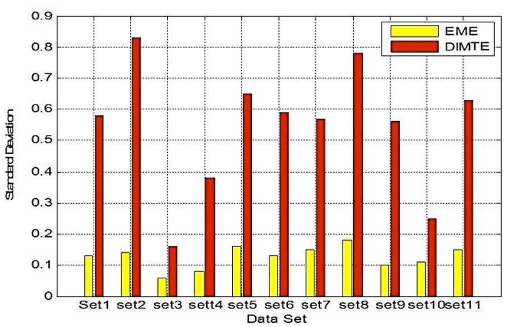


Fig. 2- Comparison between EME and DIMTE

In table 6 comparisons of the proposed methods and the well-known $EME = \frac{1}{k_1k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\frac{I_{max;k,l}}{I_{min;k,l}}$ measure in aspect of standard deviation, STD, and MOS characteristics are represented:

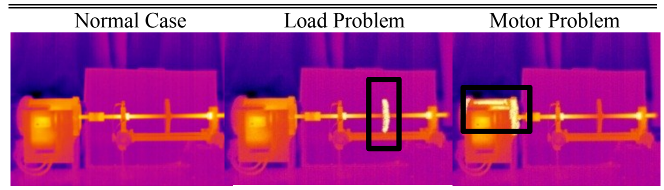
Table 6- Comparison of measures –MOS and STD characteristic

	EME	DMTE	DIMTE	MDIMTE
STD	0.03	0.07	0.21	0.25
MOS	3.51	3.82	4.12	4.25

Table 6 shows that the proposed algorithms have more STD and MOS than EME and it means that their performances are better due to make the large difference among images with different qualities.

Application

Fault Detection. Thermal imaging is currently applied to machine condition monitoring and diagnosis field. The proposed measure could be applied as fault detection during system maintenance [27]. Consider a case scenario when a shaft problem in a DC motor causes to rotate it faster which causes temperature increase. In a thermal imaging monitoring system the proposed measure will help to detect temperature anomalies and alert a system malfunction. In the following thermal images for a motor for two different cases are illustrated. The results in Fig 3 show that the measure detects differences between the "normal" and "failure" scenarios for motor overload scenario. In this experiment number of blocks has been chosen as 3×3. The load problem and motor problem is artificially added to the original image [28-29] and the proposed measure is applied on them. The results are illustrated in Fig. 3. The matrices A, B and C are the values of applying our proposed measure on each block before the final step of averaging the measure on all blocks. By subtracting the B and C matrix form the original one you can find that a problem happened for the second and third images and the location of fault is also could be determined. It is obvious that by dividing the image into more blocks the results created in more details.



$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0.0002 & 0.0057 & 0.0065 \\ 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 0 & 0 \\ 0.0001 & 0.0060 & 0.0541 \\ 0 & 0 & 0 \end{bmatrix} \quad C = \begin{bmatrix} 0 & 0 & 0 \\ 0.1277 & 0.0057 & 0.0065 \\ 0 & 0 & 0 \end{bmatrix}$$

Fig. 3- Thermal Imaging application-Fault Diagnosis [29]

The described thermal imaging based fault diagnosis can be also used as a part of a general control structure as illustrated in Fig.4:

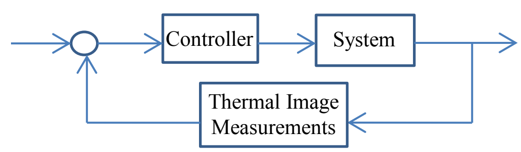


Fig.4 Control System Application

In such a system, if the load of a motor problem exceeds a specified threshold, then the thermal measuring system sends a feedback alarm to the controller. The feedback signal to the controller contains both temperature and its distribution which helps to localize temperature anomalies.

4-Conclusion

In this paper, thermal measurement systems for image quality assessment are introduced. It is demonstrated that the proposed methods are applicable for both color and gray thermal images. The first assessment measure is based on integration of human visual system and density based measure. The second measure is a combination of features accounting for human visual system and information system and distribution based measure. The introduced measures could be used in many applications. Fault detection, monitoring, maintenance, and control of machine system are represented as application of the proposed measurement system. The results demonstrated high performance of the presented measurement system in improving the visual quality of the thermal images.

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