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Energy Efficient Image-Based Target Recognition Using Fourier Descriptors in Wireless in Multimedia Sensor Networks

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Abstract: Multimedia communication is highly attractive and desired by many applications due to the wealth of information provided. However, the transmission of image and video data streams needs a specific scheme to meet the limitations of the sensor node. In depth, the performances of multimedia-based applications on WMSN are highly dependent on the capabilities of the designer to provide low-power data processing and energy-aware communication protocols. The compression techniques applied for sensed data required extensive resources and high computational capabilities, which contrary the sensor's resource constraints explicitly. One of the best ways to reduce the energy consumption per-node and to extend the network lifetime is to use a local event-based sensing approach for the detection of relevant phenomena to be reported to the end user. In this method, the sensor checks whether the image captures the phenomena of interest locally at the sensor node and notifies the remote end user with the transmission of the minimum required data. This work contributes a design for object detection and recognition scheme based on the use of Fourier Descriptors for image feature extraction. This paper is an extended version building on the results already presented in [17]. This current paper is an outline the specification of the proposed scheme and its implementation on wireless multimedia sensors. It addresses the performances' evaluation regarding time and energy consumption. The experimental results reveal the high levels of accuracy of the proposed approach in efficiently recognizing the target and notifying the end user. It shows a significant performance that overcomes the efficiency of similar sensing approaches based on Zernike Moments that have been proposed in the literature.

Keywords: WMSN, Multimedia sensing, Object recognition, Low-power, Fourier descriptors, Zernike moments.

1. Introduction

The evolution of micro-electro-mechanical systems (MEMS) technology, wireless communications, and digital electronics have created a low-cost solution for data collection [1-2] using a distributed system based on sensors. These systems are called Wireless Sensor Network (WSN). They are composed of a set of small devices called sensors nodes. The wireless sensors will cooperatively monitor their environments in a self-organized way. The data gathered by this sensor is transmitted by multi-hop wireless mode, through a sink node, to the end user for further evaluation and processing. A sensor node based on a microcontroller for the processing tasks, and it has a limited memory storage capacity, a wireless communication module, and some sensors for different physical measurements such as

temperature. Sensor nodes are in general self-powered using an embedded battery with insufficient energy which makes energy-scaring massive data processing and communication [2-3].

The availability of low cost embedded devices for multimedia sensing has encouraged their integration with low-power wireless sensors to create these inexpensive systems referred to as WMSNs. These networks allow retrieving multimedia streams, storing, processing them in smart ways for intelligent applications [4]. Due to the attractive characteristics of multimedia contents [5-6] to provide visual verification, in-depth situational awareness, recognition, and other capabilities. The deployment of these communication infrastructures has received increasing attention in the research community level [4].

Multimedia applications characterized by producing a high data volume that give a potential risk in the resident energy of network sensors. Thus, the design of multimedia sensing application should take in consideration energy efficiency. The design of applications based on WMSNs influenced by a prodigious number of factors that considered as technical challenges and characteristics of WMSNs [7]. These challenges include an application-specific quality of services (QoS) requirements, scalable and flexible designs and protocols to support heterogeneous applications, high bandwidth demand, localized processing and data fusion, efficient energy design, reliability and fault tolerance, multimedia coverage, and models for programmability. The development of these communication systems constitutes an interdisciplinary research area. It integrates communication architecture with signal processing and information theory along with the design of embedded and distributed processing systems. Thus, the design of an efficient solution for communication in WMSN impacted by different factors that considered as technical challenges. In fact, many qualities of service requirements need to be considered for specific-applications using WMSN. The scalability is also an important issue for the design of the sensing and communication approach in these networks to provide flexible architectures and protocols to support heterogeneous applications, localized processing, and data fusion.

Several previous research contributions [5-6], [8-9] have addressed this issue of energy efficiency with the application of different approaches such as data compression and the design of hardware co-processors. Others have proposed collaboration of the nodes [10-13] to perform multimedia sensing. The extraction of the Region of interest (ROI) was suggested as an attractive approach for low-energy multimedia networking in WMSN [10], [14-16]. Even though some of these solutions demonstrated attractive energy saving, we think that research work is still required to define a suitable solution for efficient target recognition that can be deployed to extend the network lifetime.

The deployment of WMSN for remote image-based target recognition and tracking applications face the problem of energy efficiency that raises the need to design a specific low-power sensing scheme and also the problem of an efficient network architecture for the processing of this scheme. An excellent approach to minimize per-node energy consumption and to extend the lifetime of a network is to use a local event-based detection scheme [15-16].

The use of a shape descriptor would help to verify in local whether the image captures phenomena of interest and then a notification with efficient data representation would help to unload the network from heavy traffic. In depth, this approach requires image-based detection of a new object, recognizing the target and notifying the end user with the minimum number of bytes to increase the network lifetime [15-16].

This paper is an extended version building on the results already presented in [17]. The main contribution of this paper is to present a promising new multimedia sensing-scheme in detail, based on the concept of event detection, employing 2D General Fourier Descriptors as the feature's extraction method. The novelty of this scheme is its ability to reduce communication overheads and per-node power consumption, while also ensuring efficient notification to the end user. Furthermore, it addresses the performance of this scheme about efficient detection and low-energy processing. This paper presents comparisons with related solutions and demonstrates the power of the proposed concept.

2. Related Work

The compression techniques applied to sensed data allow reducing the number of packets that transmitted to the end user through the network [5-6]. It aims to reduce per-node energy consumption related to the wireless transmission and to unload the network from substantial amounts of data. Consequently, it will help to extend the network lifetime and reduce congestion, which will enhance the quality of service from the end user point-of-view. However, the earliest studies have shown that most of the well-known compression algorithms developed for computer-based applications were not applicable in the context of WMSN. Most of them required extensive resources and high computational capabilities, which contrary to the sensor's resource constraints [10] explicitly.

Many solutions for image compression were inspired mostly from JPEG2000, discrete wavelet transformation (DWT) [18] compression techniques, and discrete cosine transformation (DCT) [19]. In the [18], a framework for multimedia compression in WMSNs presented. The used compression algorithm based on the DWT. The sensed data are reduced based on multiple stages of this compression technique to meet a certain level of resolution based on the end application demand. The network organized into multiple levels where each level split the sensed data into four data blocks. Each block associated with a

cluster head network node that is responsible for applying a real-time filtering scheme for extracting the temporal summarization. Huffman coding applied to the compressed data from all four blocks and, then, passed to the 3D-DWT compression algorithm. Finally, the process should be repeated until a certain level of resolution is obtained, and the data will be forwarded to the sink node. This method achieved an efficient, on-demand compression resolution level. However, the main drawback of this work is the high computational cost regarding iterated compression processes.

In [19], the presented multimedia compression approach for WMSNs is intended to solve the high computational cost of the solution presented in [18] using a 2D-DCT compression technique. The sensed data is subject to the 2D-DCT compression algorithm in the first level only instead of an iterated process. This advantage promotes this solution to an excellent compression implementation in constrained resource sensors.

In [20], authors decreased the algorithm's computational complexity by applying the zonal DCT compression technique. However, this work suggested a hardware implementation, which is not considered a scalable solution for implementation in wide-scale sensor networks because it raises up the implementation cost.

There are some contributions to literature addressing the design of efficient image-based techniques for object recognition. In the literature, there are many shape descriptions and techniques to measure similarity. These techniques summarized in [21]. They classified some approaches to the extraction and representation of shape-based features according to their processing methods. This survey concluded GFD techniques to be highly efficient and accurate for object recognition.

The General Fourier Descriptors (GFD) technique described as a very efficient and accurate solution for object recognition [16], [22]. GFD not studied regarding object detection and recognition in wireless multimedia sensor networks [22]. Thus, we think that a research effort is still required to define a well-distributed processing scheme for image-based target recognition. The advantage of this kind of application would reduce per-node energy consumption and extend the network lifetime.

The motion detection framework presented in [23], is developed for WMSNs to be applied in areas of surveillance. The method divides the captured image into sets of small blocks. Then, the framework examines any differences between the blocks of the captured image and the reference image. This approach helps not only to save energy but also to keep bandwidth usage low. However, it can be applied only in the context of object appearance detection, not in object identification or classification.

In [24], they have used the Haar wavelet for object feature extraction, but they did not address the scheme's computational complexity and the energy consumption efficiency with the adoption of WMSN. Zuo, *et al.* [25] presented a distributed two-hop, clustered-image transmitting scheme. The approach based on two types of sensor nodes: normal sensor nodes and camera-equipped nodes which acted as cluster heads, which distributed the compression's tasks to the nodes of the cluster. The other nodes participated in the distributed compression scheme as well as in the transmission process. This approach worked to balance the power consumption between the cooperated nodes, which extended the whole network lifetime. However, the transmission of a stream of images still exhausted the network's energy and increased the contention and congestion in the network. We believe that such a compression scheme can be applied to transmit just the image of the specific target required by the end user. In [26], authors employed hardware platforms for power conservation which have a high implementation cost and made no consideration of a scalable solution. In [27], a new scheme, based on a quad-tree decomposition for image compression, is presented. The authors suggested it was an efficient low-power solution in WMSNs. In [28], an artificial immune system-based image pattern recognition method was presented, but the associated energy consumption was very high; therefore, we think that it is not suitable for low-power processing.

3. Image-Based Sensing Scheme for the Target Recognition

One attractive method of minimizing power consumption and extending the network lifetime is to employ a local event-based sensing and detection scheme. A way to accomplish this method is the use of the Region of Interest (ROI) descriptor to detect if the image captures phenomena of interest locally at the sensor node and to send the minimum required data to the end user. This approach reduces the data transmitted to the sink node; consequently, it preserves the energy of the source sensor as well as the energy of the other nodes of the network [15-16]. This method based on notifying the end user solely when phenomena have been detected in the observation scenes. The adoption of this technique requires designing an efficient image analysis method to detect the target with invariance for translation, orientation, and scaling properties.

In WMSNs, the starting point for object identification and detection is the extraction of the essential shape features. The shape-based features provide a compact representation that is suitable for storage and communication.

In the analysis of the available solutions indicates the designing of a new, efficient, and scalable scheme for image-based sensing should satisfy:

1) Low computational complexity;

2) High accuracy;

3) A lower level of required memory storage;

4) A network congestion reduction via limiting the per-node communication overhead.

In this approach, sensors are supposed to be pre-configured to recognize a specific target using its shape descriptors. These processing sensors will be loaded by end application with a reference's signature (i.e., target's feature vectors). This signature will be used later in the matching phase after extracting the ROI set of feature vectors (see Fig. 1).

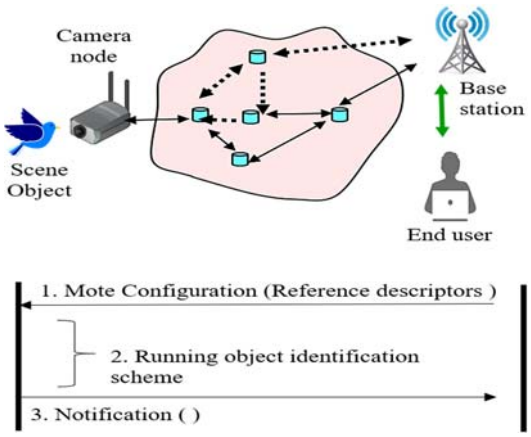


Fig. 1. Event-based object detection and recognition scheme in WMSN.

Then, multimedia sensor periodically senses the surrounding environment. Once an event is detected, a sensor starts the object detection and extraction process from the captured scene. A feature extraction method will be applied to obtain a set of features' vectors that will be compared with a previous version of the features of the target. A notification will be sent to the end user when the matching process indicates significant similarities. Otherwise, the sensed event is discarded, and the camera sensor resumes the search for an event (see Fig. 2).

The following part of this section moves on to describe, in great detail, the structure of the proposed object detection and recognition scheme. The underlying assumption of this approach is the reduction of node communication activities through the radio link while increasing local processing activities. Thus, the capacity of this scheme to extend the per-node lifetime depends on the complexity of the different tasks involved during the processing cycle of the detected object.

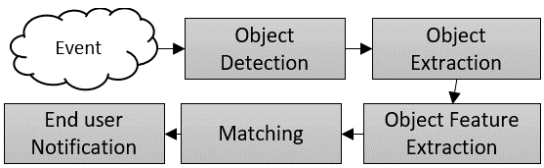


Fig. 2. Structure of the image-based sensing scheme based on GFD [17].

The structure of the proposed scheme consists of sequential steps as outlined below.

3.1. Detection of New Object

In this essential step, to detect the new object, we based on the background subtraction technique presented in [9]. The experimental demonstration of this method was first carried out by [9]. This method is useful when the background rarely changed. Also, it has a low computational complexity to isolate the ROI from unfeasible background data.

This technique splits the image into a set of blocks of eight by eight pixels. The variance between the new image and the background image measured by the variance of the pixel intensity level. If the foreground block is noted by $\beta_n(j)$ and background $\beta_{n-1}(j)$ respectively, then when the whole difference through all the image blocks is more significant than a certain threshold (T_{ther}), a new object should be detected, as expressed in (1).

$$\sum_{j=1}^{k} |\beta_n(j) - \beta_{n-1}(j)| > T_{ther} \quad (1)$$

3.2. Extraction of the Region of Interest

As a result of the background subtraction procedure, we will get a data area to contain the region of interest (ROI) which represents the useful information besides to the null data which represent the empty subtracted background area. As a result, there is an urge to detach this region to minimalize the processing complexity. The scheme will start extracting the ROI blocks and separate them from additional and worthless blocks. Later, those extracted blocks will be changed to binary representation as a preparation step for the feature extraction technique. (see Fig. 3).

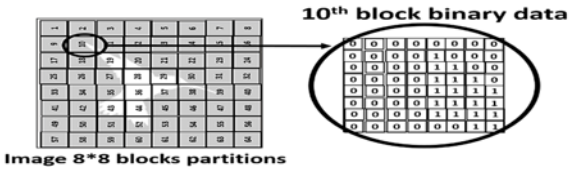


Fig. 3. Binarizing useful extracted blocks [17].

This step reduces both the memory occupancy and energy consumption related to pixel processing.

3.3. Extraction of Feature's Vectors

An efficient sensing scheme for object identification in WMSN is essential for the consideration of limitations and challenges. When a new object is detected, the sensor has to decide whether it is the tracked object using the feature's descriptor of the object. The primary design challenge

when implementing this approach is the specification of an efficient low complexity scheme capable of identifying targets with low-power and low-memory occupancy cost. The process of extracting the features of the detected object show a significant role in the overall performance of the identification scheme. Some metrics have to be considered while designing this task:

3.3.1. Low Sensing Power Consumption

Based on the design specification of sensors, the algorithm complexity has a direct impact on the residual energy level [9]. The internal processor and transmitter consume a considerable proportion of power from the overall sensor resident battery. In computational theory, there is a proportional relationship between the total number of processor clock cycles and the arithmetic and logic operations undertaken in a microprocessor [5-6].

3.3.2. Preserve Memory Capacity

Wireless multimedia sensors have limited memory; therefore, to ensure optimal multimedia processing, the designer would have to ensure that memory occupancy kept as low as possible. In WMSN, multimedia sensors are equipped with a particular type of memory specified for the captured data only but not for the processing operations [4, 7], [10]. In our scheme, we reserve the memory by dealing with a minimum number of signatures features instead of the whole captured image. These features being expressed in restricted data size (i.e., one feature vector requires eight bytes, ensuring that thirty-six feature vectors are required for 288 bytes).

3.3.3. Communication Overhead

The feature vector that represents the object descriptor has to be as short as possible. In fact, the memory constraints of the motes and the low bandwidth that is available in the WMSN make it preferable to retain the shortest feature vector that would allow efficient target identification. This approach favors scalability for the dynamic run-time changing of target objects. Using a small vector datatype representation is a favorite choice for limited bandwidth [7, 11]. It is significant can decrease the communication overheads, while also minimizing traffic over the bandwidth in comparison to sending total image bytes or employing the compression method.

The shape-based recognition methods are desirable to achieve low complexity and high efficiency [15-16]. These advantageous properties correspond well with our design mentioned above considerations. The features extracted based on the shape methods can achieve invariance to many factors like rotation scales and translation. Besides, the size of the vector can be adjusted to keep a trade-off between the efficiency of identification and the memory constraints.

In WMSNs, the starting point for object identification and detection is the extraction of the essential shape features. The shape-based features provide a compact representation [21, 29] that is suitable for storage and communication. In the literature, there are many shape descriptions and techniques to measure similarity. These techniques summarized in [21].

However, a minor set is capable of being adapted in WMSN due to the constraints of the sensor node's design. These limitations are alienated into two aspects:

1) Low processability;
2) Restricted memory capacity.

Further approaches can be adapted for use in the context of WMSN, but these require certain modifications in node design, which raise the cost of implementation, resulting in imperfect scalability.

In our proposed scheme, the end user has to generate the object descriptors, which they are required to identify the target in the area of surveillance. At the configuration step, the data representing this object will be transmitted to the dedicated wireless multimedia sensor through the network using a specific protocol for dynamic configuration.

There are many shape transforms are used nowadays in Digital Image and Signal Processing researches. In this work, we based on General Fourier Descriptor (GFD) for extracting a set of signature's features vector. It is one of shape classification and description approach [21-22], employed in a large number of application fields based on image processing, due to:

1) Ease of computation;
2) Low complexity;
3) Robustness to noise;
4) Compactness.

From a mathematical perspective, a comparison with Zernike Moments (ZM) (i.e., a well-known technique for describing shapes [29]) reveals that GFD has no redundant features because there is no repetition and it permits examination of features in both radial and angular directions [21-22]. These are also compared in the implementation section below from the perspective of in-node power consumption.

GFD is primarily deployed to transform the shape signature using Fourier transformation based on the signature region. The algorithm based on the introduced polar pixel tiling scheme instead of Cartesian coordinates [30]. This technique yields not to show the geometric error and numerical integration error which are essential in Cartesian coordinates. This step profits an affected enhancement in accuracy of Fourier descriptors results.

The ROI is mapped to the unit disc through polar coordinates, where the center of the ROI is the origin of the unit disk. The conversion from rectangular to polar coordinates is done through Equation (2) and

Equation (3). The length of the vector then describes the coordinates from the origin of the disk to the coordinate point and the angle from the x-axis to the polar radius. The pixels falling outside the unit disc are not used in the calculation.

Firstly, GFD transforms the input image $f(x_i,y_i)$ of size N×M where f defined by $\{f(x_i,y_i)$: $1 \leq i \leq M$, $1 \leq j \leq N\}$ into a polar image $f(r,\theta)$ using the following equations [22]:

$$r = \sqrt{(x - \acute{x})^2 + (y - \acute{y})^2} \quad (2)$$

$$\theta = tan^{-1}\left[\frac{y - \acute{y}}{x - \acute{x}}\right], \quad (3)$$

where $\acute{x}$ and $\acute{y}$ are the mass center of the shape. The following equations calculate them [22]:

$$\acute{x} = \frac{1}{M}\sum_{i=0}^{M-1} x_i \quad (4)$$

$$\acute{y} = \frac{1}{N}\sum_{i=0}^{N-1} y_i \quad (5)$$

Secondly, the Fourier transformation takes place to extract the signature feature vector set, referred to as Fourier Descriptors (FD), using the following equation [22]:

$$FD(\rho,\varphi) = \sum_{r=0}^{R}\sum_{\theta_i=0}^{T} f(r,\theta_i)e^{j2\pi\left(\frac{r}{R}\rho + \frac{2\pi i}{T}\varphi\right)}, \quad (6)$$

where ρ and φ reflect the image size, $\theta_i = \frac{i2\pi}{T}$, $0 \leq \varphi < T$ and R is radial resolution and T is angular resolution.

The variants' properties can be eliminated based on the concept of algebraic invariants as in the following equation [22]:

$$GFD = \left\{\frac{|FD(0,0)|}{area}, \frac{|FD(0,1)|}{|FD(0,0)|}, \ldots, \frac{|FD(0,n)|}{|FD(0,0)|}, \ldots, \frac{|FD(m,n)|}{|FD(0,0)|}\right\}, \quad (7)$$

where m is the maximum number of radius frequencies, and n is the maximum number of angular frequencies.

Zhang, *et al.* [22] recommended twenty-four GFD features, reflecting four radial frequencies and nine angular frequencies.

3.4. Target Identification

When a new object is detected, the sensor has to decide whether it is the tracked object using the feature's descriptor of the object. In the presented scheme, we rely on Mean Square Errors (MSE) for measuring the similarities between the set of the features vector of captured scenes and the pre-configured reference feature vector set. The MSE equation measured as follows:

$$MSE = \frac{1}{n}\sum_{I=1}^{n}(x_i - \bar{x}_i)^2 \quad (8)$$

where n represents the total vector set, x_i denotes the i_{th} feature vector of the extracted signature and $\bar{x}_i$ denotes the i_{th} feature vector of reference.

The similarities are an estimate based on a certain threshold number. If it is less than certain threshold $T_{Difference}$, the detected object is declared as the target, and the sensor notifies the user. Otherwise, the detected object does not represent useful information to the end user, and the image will be ignored.

3.5. End User Notification

The algorithm running in the Wireless Multimedia Sensor should be able to detect a new object that appeared in its surveillance area and should decide whether it is the target object. Based on the requirement specified by the application, the sensor might decide to send an object detection notification in the form of a simple byte [15-16]. Alternatively, the sensor might send the descriptor or extract useful information representing the scene to send to the end user. According to the remote end user's applications, the notification will be served.

Thus, this step represents the potential for achieving a substantial saving in time and power-consumption by sending a single byte message, a set of feature vectors or useful extracted blocks from the image. On-demand notification requests by the end user relieve the bandwidth from congestion by minimizing both the volume of transmitted data and the need for retransmitting in case of error. The approach leads to a light heavyweight traffic's load, this will prolong the life of the entire network.

4. Implementation and Performance Analysis

In this section, the empirical effectiveness of the proposed approach is investigated. We illustrate it from two different perspectives, namely, the target recognition capability and the algorithm complexity and time response of the sensing scheme. The algorithm design will be validated through simulation and by testing its performance using the MATLAB and AVRORA simulator [31] for WSN. Simulation results will be used to determine the algorithm's accuracy in identification of the signature's features and its resources' requirements regarding memory and power consumption.

4.1. Target Recognition and Performances Analysis

In this section, we provide a summary of the performance results related to power consumption and the processing time of the proposed scheme for object detection and identification when implemented on MICA2 wireless motes. For comparison reason, the performance analysis approach used in this investigation is similar to that used by [15-16]. We built up the recognition algorithm in the MATLAB to assess the efficiency of the selected shape descriptor. This step is vital to prove the algorithm invariance property and accuracy for target recognition. Besides, we will attest to the algorithm using the AVRORA simulator [31] to show how the presented scheme can satisfy the requirements of WMSN design.

A set of test images in [16] was employed to evaluate and compare the capability of the scheme in target recognition to recognize an object under different invariance conditions, i.e., rotation, scale, and translation. The images employed in the experiment of 64×64 and 128×128 grayscale eight bpp. In Fig. 4, we demonstrate the test image set, which was composed of twelve images. Based on the recommendations of [22], the GFD radiance frequencies where set in the Equation (6) to three, and angular frequencies to eight, thus giving a total set of twenty-four different features' vectors. The features of these objects were employed to calculate the similarity with the reference target-image features vectors, using MSE to identify the target.

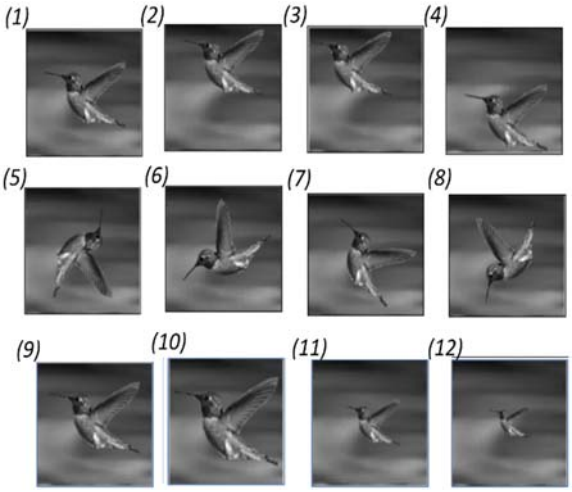


Fig. 4. Testing images set: (1) the original reference; (2) Translated object to up; (3) to corner; (4) to down; (5) Rotated object by 30°; (6) by 55°; (7) by 65°; (8) by 90°; (9) the maximize object by 55 %; (10) by 65 %; (11) the minimize object by 25 %; and (12) by 35 % [17].

In Table 1 and Table 2, we present the extracted feature vectors computed using MATLAB using GFD [17] and ZM [16] techniques, respectively. These are feature vectors associated with the image set on Fig. 4. in this table, GFD and ZM results are invariants under shifting, rotation, and scaling.

Table 1. Set of extracted feature vectors based on GFD.

Vector	Original	Top	Corner	Down	Rotate 30	Rotate 55	Rotate 65	Rotate 90	Scale 25	Scale 35	Scale 55	Scale 65
1	0.1945	0.1777	0.1820	0.1876	0.1981	0.2001	0.2183	0.1849	0.1712	0.1894	0.1872	0.1972
2	0.0742	0.0828	0.0713	0.0637	0.0432	0.0725	0.0733	0.0630	0.0555	0.0664	0.0619	0.0697
3	0.0376	0.0957	0.1069	0.0739	0.0502	0.0855	0.0970	0.0467	0.1788	0.1047	0.0634	0.0372
4	0.2564	0.2634	0.2595	0.1776	0.2153	0.2304	0.2366	0.2656	0.2236	0.2422	0.2517	0.2412
5	0.1627	0.1354	0.1364	0.1922	0.1749	0.1551	0.1776	0.1739	0.2080	0.1858	0.1470	0.1616
6	0.0257	0.0376	0.0396	0.0153	0.0287	0.0501	0.0419	0.0380	0.0698	0.0404	0.0362	0.0189
7	0.0612	0.0539	0.0719	0.0639	0.0651	0.0056	0.0152	0.0629	0.0641	0.0510	0.0365	0.0492
8	0.1158	0.1370	0.1230	0.0586	0.0763	0.0741	0.0812	0.1347	0.0967	0.1101	0.1264	0.1185
9	0.0607	0.0646	0.0554	0.1018	0.0581	0.0843	0.0848	0.0452	0.1227	0.0733	0.0555	0.0625
10	0.0349	0.0175	0.0246	0.0511	0.0355	0.0206	0.0361	0.0490	0.0463	0.0523	0.0247	0.0175
11	0.3615	0.3612	0.3321	0.3279	0.3575	0.3647	0.3539	0.3258	0.3921	0.3728	0.3538	0.3376
12	0.1139	0.1989	0.1992	0.1213	0.0971	0.1415	0.1449	0.1719	0.1222	0.1104	0.1475	0.1258
13	0.1160	0.0696	0.0556	0.1266	0.1237	0.1731	0.1586	0.0704	0.1750	0.1421	0.1324	0.1179
14	0.1827	0.1601	0.1583	0.1241	0.1484	0.1276	0.1553	0.1620	0.1377	0.1710	0.1408	0.1627
15	0.0996	0.1132	0.1110	0.1355	0.1403	0.1431	0.1292	0.0729	0.1967	0.1374	0.1102	0.0882
16	0.0739	0.0721	0.0969	0.0666	0.0727	0.0828	0.1049	0.0960	0.0901	0.0655	0.1036	0.0870
17	0.0366	0.0413	0.0456	0.0999	0.0495	0.0724	0.0634	0.0520	0.0910	0.0572	0.0670	0.0410
18	0.0686	0.1072	0.1010	0.0565	0.0624	0.0739	0.0794	0.1036	0.0291	0.0539	0.0566	0.0706
19	0.0744	0.1041	0.0951	0.0862	0.0918	0.0778	0.0648	0.0650	0.1074	0.1008	0.0722	0.0606
20	0.1085	0.0972	0.1122	0.0806	0.0815	0.0762	0.0813	0.1139	0.0521	0.0729	0.1223	0.1264
21	0.1003	0.0883	0.0651	0.0857	0.1020	0.0667	0.0739	0.0775	0.1372	0.0964	0.1278	0.1055
22	0.0362	0.1163	0.1106	0.0567	0.0549	0.0473	0.0401	0.1276	0.0782	0.0480	0.0698	0.0465
23	0.0680	0.0793	0.0771	0.1029	0.0636	0.0866	0.0791	0.1052	0.0596	0.0500	0.0627	0.0731
24	0.0809	0.0504	0.0329	0.0610	0.0471	0.0810	0.0921	0.0120	0.0640	0.0763	0.0581	0.0696
25	0.0523	0.0391	0.0280	0.0280	0.0630	0.0704	0.0573	0.0208	0.0856	0.0788	0.0497	0.0364

Table 2. Set of extracted feature vectors based on ZM.

Vector	Original	Top	Corner	Down	Rotate 30	Rotate 55	Rotate 65	Rotate 90	Scale 25	Scale 35	Scale 55	Scale 65
1	0.1021	0.1005	0.098	0.0995	0.1037	0.1007	0.1106	0.0979	0.0866	0.1938	0.1209	0.172
2	0.0008	0.0008	0.0007	0.0008	0.0008	0.0002	0.0007	0.0007	0.0838	0.0749	0.0902	0.0794
3	0.217	0.2088	0.209	0.2087	0.2249	0.221	0.2383	0.2035	0.0681	0.2773	0.1523	0.2608
4	0.0035	0.008	0.0082	0.007	0.0046	0.0051	0.0063	0.0043	0.0696	0.0396	0.0595	0.0421
5	0.0211	0.0223	0.0187	0.0248	0.0166	0.0159	0.0197	0.0227	0.063	0.0544	0.1052	0.0926
6	0.0158	0.0193	0.0117	0.0184	0.0124	0.0138	0.0166	0.017	0.0469	0.0035	0.0261	0.0083
7	0.1844	0.1671	0.1905	0.1682	0.2034	0.2021	0.2124	0.1605	0.0712	0.2114	0.1108	0.2001
8	0.0128	0.0187	0.0267	0.0156	0.018	0.0232	0.0299	0.0069	0.0638	0.1041	0.0906	0.0827
9	0.0136	0.0138	0.0152	0.0128	0.0142	0.0118	0.0144	0.0139	0.0259	0.0711	0.0272	0.0495
10	0.0609	0.0757	0.0565	0.0759	0.052	0.0516	0.0617	0.0708	0.0424	0.0482	0.0429	0.0187
11	0.0515	0.0616	0.0355	0.0587	0.0396	0.045	0.0524	0.057	0.0554	0.0473	0.0548	0.0333
12	0.0052	0.0063	0.0071	0.005	0.0056	0.0038	0.0058	0.0066	0.0313	0.0903	0.0495	0.0675
13	0.0899	0.0779	0.1239	0.0716	0.1174	0.115	0.1187	0.0686	0.1059	0.1938	0.1361	0.2133
14	0.0249	0.0166	0.0403	0.0164	0.0306	0.0465	0.0606	0.0081	0.0376	0.0984	0.0684	0.0617
15	0.0451	0.0474	0.0475	0.0443	0.0467	0.0411	0.0477	0.0488	0.0311	0.0778	0.0119	0.0668
16	0.0054	0.006	0.0069	0.0057	0.0046	0.0047	0.0063	0.0052	0.0486	0.0451	0.0575	0.0439
17	0.0743	0.0965	0.0697	0.0949	0.0617	0.0752	0.083	0.0853	0.0849	0.0776	0.024	0.04
18	0.0819	0.0856	0.0545	0.0832	0.0643	0.0732	0.0816	0.0858	0.0541	0.0445	0.0426	0.0309
19	0.0154	0.0228	0.0179	0.0182	0.0154	0.0109	0.0153	0.0226	0.0059	0.1201	0.0356	0.1004
20	0.0043	0.0051	0.0028	0.0052	0.0035	0.0039	0.0046	0.0038	0.059	0.0162	0.0508	0.03
21	0.0035	0.0137	0.0443	0.0052	0.0233	0.0218	0.0177	0.004	0.0755	0.1765	0.167	0.2301
22	0.0287	0.0209	0.0319	0.025	0.031	0.0518	0.0618	0.0245	0.0353	0.0748	0.066	0.0629
23	0.063	0.064	0.0643	0.0617	0.0661	0.0649	0.0702	0.071	0.0444	0.0673	0.021	0.0727
24	0.0177	0.0222	0.0215	0.0203	0.0143	0.0149	0.0191	0.021	0.0259	0.0682	0.0515	0.065
25	0.0027	0.0027	0.0032	0.0022	0.0035	0.002	0.0028	0.0029	0.0591	0.016	0.0331	0.0052

In Fig. 5 and Fig. 6, we test the invariance property of GFD and ZM. As shown, the x-axis represents the number of feature vectors we obtain for all the twelve-test image set where the y-axis represents the value of the obtained feature vector. We conclude from the plots that all curves are almost identical to the reference image. We are using the MSE to measure statistically the similarity based on the deviation from the signature features' vector. What is interesting in these figures is the identical general patterns of the GFD results to ZM results in those reported by [16]. The result shows that the GFD Invariants are more superior in all aspects.

However, GFD reveals more accurate results than ZM with a difference of less than 1. This outcome is due to the ZM mathematical nature which is invariant only to rotation property. To accomplish the whole invariance properties (i.e., scaling and translation), ZM needs A pre-processing step to normalize the object to a set the object into the center and to return it to a predefined scale ratio. However, this step will raise the computation complexity of the algorithm.

In contrast, the GFD accomplish the invariant property based on the normalization Equation (7) that drives the GFD ability to be invariant to all object translation, scaling and rotation, thus resulting in lower processing complexity and energy consumption than in ZM.

In Table 3, to prove the accuracy of recognition capabilities of ZM and GFD, we summarized the deviation based on MSE between the signature and captured images under different variance position and size. This result reveals a high accuracy in acknowledging that the target with MSE almost equals zero under different positions, including translation, rotation, and scaling.

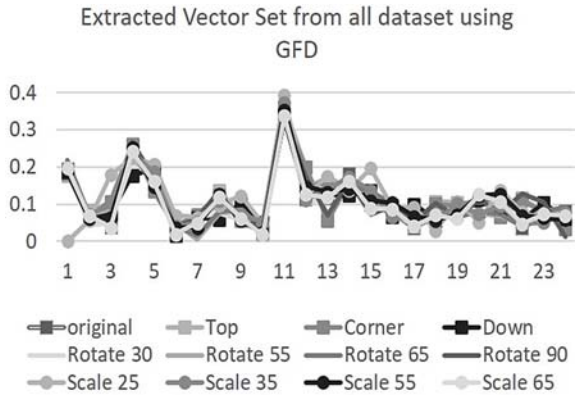


Fig. 5. Extracted vector set using GFD [17].

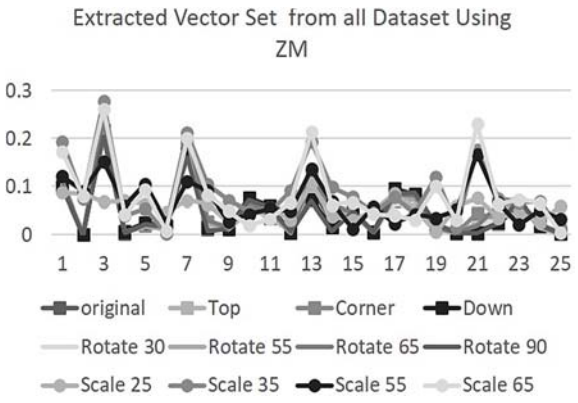


Fig. 6. Extracted vector set using ZM [17].

Table 3. An invariance property of ZM and GFD under Translation, Rotation, and Scaling [17].

Image Number	Mean Square Error (MSE)	
	ZM	GFD
2	0.0001	5.410-06
3	0.0001	3.00E-06
3	0.0002	9.10E-07
4	0.0001	2.50E-07
5	0.00001	6.00E-07
6	0.0002	1.10E-05
7	0.0001	1.80E-06
8	0.0004	1.00E-05
9	0.0007	1.00E-06
10	0.0045	1.40E-07
11	0.0004	1.00E-05
12	0.0048	5.10E-07

ZM is very sensitive to the noise in the image, and due to the re-scaling process applied on the captured image will lead to having some loses in image pixels' intensity. While in GFD, this noise is absent due to the mathematical-based normalization process. We conclude based on this table that GFD is overridden the ZM in term of accuracy and ease of computation. GFD feature vectors contain less deviation from the reference vector set in comparison to ZM results, and for scaled images. These results establish that the proposed scheme provides a robust and precise technique of shape descriptors to recognize a specific target.

It also establishes a high capacity for capturing significant features of the sensed object while minimizing the complexity of the algorithm by its invariant characteristics, leading to the potential for lower power consumption.

4.2. Energy Consumption Evaluation

The design efficiency of this scheme measured by the consideration of the accuracy of target detection, energy consumption, time response, memory occupancy and the scalability. The efficiency of the proposed image-based sensing scheme for low-power target recognition should be evaluated about its capability to save energy in the camera node, consequently extending the lifetime of the network, as well as evaluating the memory occupancy in the node. We are mainly interested in evaluating the energy consumption at the sensor's level during recognition and notification when considering various scenarios. We estimated the performance of the proposed scheme for wireless sensors (MICA2 sensors) regarding energy and time. The primary focus of this work placed on the evaluation of the processing related performances of the scheme using GFD.

We evaluated the memory occupancy related to the employ of GFD and ZM as a feature extraction technique in the proposed sensing scheme. In Table 4, we conclude using GFD instead of ZM can minimize the scheme occupancy needed from the memory storage to 7 kB (due to the equation complexity of ZM [29]).

Table 4. Memory storage for sensing scheme based on GFD and ZM [17].

Size of	ZM	GFD
Stored program text	10 kB	3 kB
Stored background image (64×64 of 8bpp)	4 kB	4 kB
Captured image (64×64 of 8 bpp)	4 kB	4 kB
Stored 24 reference descriptors (float-number)	100 bytes	96 bytes
The region of interest in binary	512 bytes	512 bytes
Extracted ROI descriptors	100 bytes	96 bytes
Total Approx	19 kB	12 kB

The proposed scheme generates a set of twenty-four different features' vectors, extracted from the image of the detected object. Each of these vectors requires four bytes to be represented in the memory, leading to a total of ninety-six bytes from the memory storage capacity. In comparison to the features extracted with ZM [16], a hundred bytes are required in the memory to store the set of twenty-four features of four bytes. Table 4 summarizes the storage required for both detection and recognition schemes.

Recent memory designs have ensured that this algorithm can accomplish a reasonable low level of storage. The AVRORA simulator for the ATmega128L microcontroller (MICA2) was employed to implement and evaluate the algorithm efficiency. AVRORA is an emulator of sensors that allows evaluating the energy consumption level associated with the internal algorithm processing based on (TinyOS). This tool determined the number of clock cycles for the Atmel series for different tasks [31]. The power consumption and processing time were subsequently estimated using the characteristics of microcontrollers for MICA2. We employed the set of images presented in the previous section, Grey-scale images of (128×128 pixels- 8 bpp) and (64×64 pixels- 8 bpp), to extract the feature's vector of the detected object with a size of ninety-six bytes as a total for twenty-four different image feature descriptors.

Table 5 and Table 6 demonstrate the processor's clock cycles, the time response, and energy cost of the main components of the proposed sensing scheme using GFD and ZM, respectively. The cost of on-node feature extraction based in the Camera-equipped MICA2 sensor, using ATmega128L for both sensing schemes. The measured energy based on the GFD for an image of size 64×64 pixels - 8 bpp is 2.59 mJ, and for 128×128 pixels - 8 bpp is 10.34 mJ. In the sensing scheme using ZM, the internal processing was 33.5 mJ and 121 mJ, respectively to 64×64 pixels of 8 bpp and 128×128 pixels of 8 bpp image sizes.

As a result, by using the sensing scheme based on GFD algorithm, we were able to outperform the sensing scheme based on ZM algorithm over 91 % reduction in total power consumption. We explained this difference in power consumption by the low-complexity of the extraction method of GFD features, which requires less pre-processing of the image.

Table 7 also shows the cost of radio transmission for extracted features assuming the use of IEEE 802.15.4 and ZigBee communication standards. The simulation program is developed using NesC language and evaluated on AVRORA, using the TinyOS platform.

Table 5. Evaluation of sensing scheme based on GFD features on MICA2.

Image size	64×64 pixels 8 bpp			128×128 pixels 8 bpp		
Measured Attribute	**Clock cycles**	**Time (s)**	**Energy (mj)**	**Clock cycles**	**Time (s)**	**Energy (mj)**
Object Detection and Extraction	442843	0.1	2.25	3403173	0.39	9.06
Feature Extraction using GFD	112205	0.015	0.34	445389	0.06	1.37
Total scheme without Notification	555048	0.115	2.79	3848462	0.45	10.43

Table 6. Evaluation of sensing scheme based on ZM features on MICA2.

Image size	64×64 pixels 8 bpp			128×128 pixels 8 bpp		
Measured Attribute	**Clock cycles**	**Time (s)**	**Energy (mj)**	**Clock cycles**	**Time (s)**	**Energy (mj)**
Object Detection and Extraction	3514284	0.47	10	14557502	1.9	43
Target Normalization	492993	0.06	1.5	1968961	0.26	6
Feature Extraction using ZM	7278526	0.98	22	23465566	3.18	72
Total scheme without Notification	11285803	1.51	33.5	28948811	5.34	121

Table 7. End user's notification types using MICA2 sensors.

Measured Attribute	Clock cycles	Time (s)	Energy (mj)
Transmit 1 byte of Notification	69569	0.01	0.3
Transmit 25 ZM Feature vectors set	7056900	1.0	30
Transmit 24 GFD Feature vectors set	6678624	0.96	28.8
Transmit region of interest (Blocks)	30610360	4.4	132
Transmit whole image with size 64 by 64	284954624	40.96	1228.8

This table illustrates different notification scenarios and their associated energy costs. In the most transmitter's energy preserving mode, a scheme can notify the end user by sending a single byte to emphasize the appearance of the looking for a target. According to the end-user application need, this notification cost can be varied regarding either send the extracted feature set (i.e., for further comparison or classification request) or send the obtained ROI.

Either choice of notification is remaining less than sending the whole image. Comparing the notification cost of the scheme based on GFD to the one based on ZM, our experiments reveal that both schemes require the same energy cost. However, the accuracy of the features extracted by the GFD method should be noted, in addition to low energy consumption in internal processing.

4.2.1. Comparison with Related Works

In comparison to similar approaches for multimedia sensing, this current scheme presents some attractive characteristics in both computation complexity and power consumption. A summary takes place below of the most relevant-reported solutions in the literature and their characteristics in comparison to the current proposal efficient solutions for low-power sensing.

This section has attempted to provide a summary of the literature relating methods described in the Section (2) compared to our scheme performance. (see Table 8).

The distributed compression scheme for WMSN, provided by Zuo, *et al.* [25], reveals very high energy

consumption for the processing and transmission of an image of 512×512 pixels equal to (1.4 J). The extraction of useful information remains more interesting than the transmission of the image, even with a compression scheme. However, the presented distributed processing fits within the context of the current scheme, to prolong the network life and it will be addressed as future work.

Table 8. Comparison between our presented scheme and similar works.

Scheme	Processing	Approach	Implement	Scalable	Complexity & Energy
Distributed Compression [25]	Distributed	Image compression	Software	yes	High Complexity and Energy Consumption
Quad-tree Decomposition [27]	Local	Decomposition and compression	Software	-	High Energy Consumption
AIS-based Solution [28]	Distributed	AI method	Software	yes	High Complexity and Energy Consumption
Prioritization scheme [26]	Local	Image blocks prioritization	Software	-	High Complexity and Energy Consumption
Object Extraction [33]	Local	Useful data extraction	Hardware	yes	High implementation cost
Centroid & Histogram [15]	Local	Useful data extraction	Software	yes	Low complexity and energy consumption
Zernike moments [16]	Local	Useful data extraction	Software	yes	Low complexity and energy consumption
Presented Solution [17]	Local	Useful data extraction	Software	yes	Very low complexity and energy consumption

Nikolakopoulos, *et al.* [27] proposed a low power complexity scheme based on quad-tree decomposition and high compression rate in WMSN. Their experiments reveal that transmits an image of size 64×64 pixels eight bpp is around 45 mJ where 128×128 eight bpp over one hop is cost 120 mJ with a compression factor of R = 0.1. This scheme is not intended mainly for event-based notification application, thus, compared to our scheme, it will load the network most of the time with unnecessary data, and it will contest the limited network bandwidth rapidly.

Wang, *et al.* [28] presented an image recognition pattern algorithm for WMSN. They based on a distributed artificial immune technique for a collaborated image recognition effort between the sensors and the base station. The experiment results confirmed a low energy consumption level but compared to our solution; it is considered a very high level of consumption. However, they failed to evaluate the performance analysis of power consumption from local processing which is essential according to our study.

In [26], Irgan, *et al.* present a WMSN compression scheme based on the image segment prioritization technique. In this work, the assessed energy consumption of this scheme is around (130 mJ). In contrast, our proposed scheme has a much lower energy cost and is more scalable.

In [33], authors provide a hardware solution for object detection and the extraction of useful information. In this work, they presented a scheme for extracting ROI based on a hardware solution, which demonstrated high-performance levels in low-complexity, but proved inflexible and was not considered as scalable.

In [15-16], both works presented schemes designed for object recognition and event-based notification. In [15], authors employed recognition methods based on centroid distance curvature features. However, the centroid distance and the curvature signatures used for the recognition capability of the presented scheme suffer from scalability and accuracy problems.

We investigated the use of Zernike moments (ZM) as a shape descriptor for target identification in WMSNs in [16]. This method has a high recognition accuracy in the term of distinguishing similar objects. It is invariant for the rotated object and to achieve the scale and translation invariant properties, Zernike moments need an object normalization process to return the shape into the center of the image coordinators and to a predefined scale ratio [32, 34]. Despite the high accuracy, this method has an iterative computation process that increases the computational complexity.

Moreover, both proposed schemes in [15, 16] built around the assumption of the single object appeared in the camera scene. In contrast, our presented scheme shows a very low complexity and high detection and recognition capability using GFD. Therefore, we concluded that the current work outperforms other solutions presented in the literature of image detection and recognition in WMSN, in the term of accuracy, efficiency, and scalability.

In conclusion, the proposed image-based target recognition using Fourier Descriptors scheme outperforms other solutions that reported in the literature. This work offers an interesting trade-off between complexity and performance to efficiently detect a target. The new scheme allows low-power multimedia are sensing in WMSNs and the evaluations of its power consumption and time

processing abilities are favorable for the event-based application. Compared to other similar methods, the proposed scheme is the most suitable regarding efficiency and scalability for object identification in WMSNs.

5. Conclusions

The focal aim of this work is to design a low-energy consumption scheme for image-based object detection and recognition to be used in the context of WMSNs. The specification and design of an energy-aware scheme for target recognition in a scene will consider the accuracy of target detection, energy consumption, time response, memory occupancy and the scalability. The proposed work in this paper used GFD invariants and formed to be superior compare ZM invariants.

We investigated the General Fourier Descriptors (GFD) for extracting a set of signature features vectors that are based on the captured image properties. It is one of shape classification and description that has been widely used in image-based applications. This method has attractive properties, such as accuracy, low complexity, robustness to noise, and compactness. The GFD is invariant to translation, scale, and rotation of the object.

In summary, we present in this work an efficient energy scheme intended to prolong the life of a network by minimizing the power consumed by both the internal processor and the transmitter antenna. The paper introduced the simulation results and compared to a scheme based on ZM, the current scheme requires less memory space for processing, and internal sensor processing saves 91 % of energy more. Moreover, a comparison of the current scheme with compression techniques discussed in the literature establishes that this scheme achieves very low processing complexity and efficient power consumption.

The idea of distributed processing of a sensing scheme over a set of nodes as a processing cluster would balance the processing over these nodes and would reduce per-node energy consumption in one sensing cycle. As a future work, we will focus on the specification and the design of a low-energy processing scheme, intended for distributed cluster-based implementation. Build-Up a scalable, fault-tolerant and energy efficient distributed processing cluster of image-based target recognition. Before such research, this current scheme will be upgraded to handle multiple target detection for simultaneous monitoring. We concluded that the concept of distributed processing as an approach to energy saving appears promising. However, the design and the implementation of a generic clustering and processing architecture is still a subject of open research.

References

[1]. W. Yang, R. Lunn, A. Tarantino, MEMS sensor-based monitoring system for engineered geological disposal facilities, *Mineral. Mag.*, Vol. 79, No. 6, 2015, pp. 1475–1483.

[2]. I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, *Comput. Networks*, Vol. 38, No. 4, 2002, pp. 393–422.

[3]. G. Tu, S. Gao, C. Zhang, Object tracking and QoS control for wireless sensor networks, *Chinese J. Electron.*, Vol. 18, No. 4, 2009, pp. 724–728.

[4]. A. Sharif, V. Potdar, E. Chang, Wireless multimedia sensor network technology: A survey, in *Proceedings of the 7th IEEE International Conference on Industrial Informatics, (INDIN'09)*, 2009, pp. 606–613.

[5]. A. Chefi, A. Soudani, G. Sicard, Hardware compression scheme based on low complexity arithmetic encoding for low power image transmission over WSNs, *AEU-International J. Electron. Commun.*, Vol. 68, No. 3, 2014, pp. 193–200.

[6]. M. L. Kaddachi, A. Soudani, V. Lecuire, K. Torki, L. Makkaoui, J.-M. Moureaux, Low power hardware-based image compression solution for wireless camera sensor networks, *Comput. Stand. Interfaces*, Vol. 34, No. 1, 2012, pp. 14–23.

[7]. I. T. Almalkawi, M. Guerrero Zapata, J. N. Al-Karaki, J. Morillo-Pozo, Wireless multimedia sensor networks: Current trends and future directions, *Sensors*, Vol. 10, No. 7, 2010, pp. 6662–6717.

[8]. M. Kohvakka, M. Kuorilehto, M. Hännikäinen, T. D. Hämäläinen, Performance analysis of IEEE 802.15. 4 and ZigBee for large-scale wireless sensor network applications, in *Proceedings of the 3rd ACM International Workshop on Performance Evaluation of Wireless Ad Hoc, Sensor and Ubiquitous Networks*, 2006, pp. 48–57.

[9]. N. Lu, J. Wang, Q. H. Wu, L. Yang, An Improved Motion Detection Method for Real-Time Surveillance, *IAENG Int. J. Comput. Sci.*, Vol. 35, No. 1, 2008.

[10]. S. Misra, M. Reisslein, G. Xue, A survey of multimedia streaming in wireless sensor networks, *IEEE Commun. Surv. Tutorials*, Vol. 10, No. 4, 2008, pp. 18-39.

[11]. W. Luo, Q. Lu, J. Xiao, Distributed collaborative camera actuation scheme based on sensing-region management for wireless multimedia sensor networks, *Int. J. Distrib. Sens. Networks*, Vol. 8, No. 8, 2012, p. 486163.

[12]. H. Wu, A. A. Abouzeid, Energy-efficient distributed image compression in resource-constrained multihop wireless networks, *Comput. Commun.*, Vol. 28, No. 14, 2005, pp. 1658–1668.

[13]. Y. Xu, H. Qi, P. T. Kuruganti, Distributed computing paradigms for collaborative processing in sensor networks, in *Proceedings of the IEEE Global Telecommunications Conference (GLOBECOM'03),* Vol. 6, 2003, pp. 3531–3535.

[14]. S.-C. Tu, G.-Y. Chang, J.-P. Sheu, W. Li, K.-Y. Hsieh, Scalable continuous object detection and tracking in sensor networks, *J. Parallel Distrib. Comput.*, Vol. 70, No. 3, 2010, pp. 212–224.

[15]. M. S. Alhilal, A. Soudani, A. Al-Dhelaan, Image-based object identification for efficient event-driven sensing in wireless multimedia sensor networks, *Int. J. Distrib. Sens. Networks*, Vol. 11, No. 3, 2015, pp. 1-11. p. 850869.

[16]. M. Al-Sabhan, A. Soudani, Efficient Event Driven Sensing in WMSN Using Zernike Moment, *Procedia Comput. Sci.*, Vol. 83, 2016, pp. 520–528.

[17]. M. Alsabhan, A. Soudani, Target Recognition Approach for Efficient Sensing in Wireless Multimedia Sensor Networks, in *Proceedings of the*

7th International Conference on Sensor Networks (SENSORNETS'18), 2018, pp. 91-98.
[18]. D. Ganesan, B. Greenstein, D. Estrin, J. Heidemann, R. Govindan, Multiresolution storage and search in sensor networks, *ACM Trans. Storage*, Vol. 1, No. 3, 2005, pp. 277–315.
[19]. Y.-C. Wang, Y.-Y. Hsieh, Y.-C. Tseng, Multiresolution spatial and temporal coding in a wireless sensor network for long-term monitoring applications, *IEEE Trans. Comput.*, Vol. 58, No. 6, 2009, pp. 827–838.
[20]. M. Leila, V. Lecuire, J.-M. Moureaux, Camera Sensor Networks, in *Proceedings of the 2nd International Conference on Image Processing Theory, Tools, and Applications, IPTA*, Paris-France, 2010, pp. 126-129.
[21]. M. Yang, K. Kpalma, J. Ronsin, A survey of shape feature extraction techniques, *IN-TECH*, 2008, pp. 43-90.
[22]. D. Zhang, G. Lu, Generic Fourier descriptor for shape-based image retrieval, in *Proceedings of the IEEE International Conference on Multimedia and Expo, (ICME'02)*, Vol. 1, 2002, pp. 425–428.
[23]. S. Belongie, J. Malik, J. Puzicha, Shape matching and object recognition using shape contexts, *IEEE Trans. Pattern Anal. Mach. Intell.*, Vol. 24, No. 4, 2002, pp. 509–522.
[24]. S. Vasuhi, A. A. Fathima, S. A. Shanmugam, V. Vaidehi, Object detection and tracking in a secured area with wireless and multimedia sensor network, in *Proceedings of the International Conference on Networked Digital Technologies*, 2012, pp. 356–367.
[25]. Z. Zuo, Q. Lu, W. Luo, A two-hop clustered image transmission scheme for maximizing network lifetime in wireless multimedia sensor networks, *Comput. Commun.*, Vol. 35, No. 1, 2012, pp. 100–108.
[26]. K. Irgan, C. Ünsalan, S. Baydere, Low-cost prioritization of image blocks in wireless sensor networks for border surveillance, *J. Netw. Comput. Appl.*, Vol. 38, 2014, pp. 54–64.
[27]. G. Nikolakopoulos, P. Stavrou, D. Tsitsipis, D. Kandris, A. Tzes, T. Theocharis, A dual scheme for compression and restoration of sequentially transmitted images over Wireless Sensor Networks, *Ad Hoc Networks*, Vol. 11, No. 1, 2013, pp. 410–426.
[28]. H. Wang, *et al.*, Artificial immune system based image pattern recognition in energy efficient wireless multimedia sensor networks, in *Proceedings of the IEEE Military Communications Conference (MILCOM'08),* 2008, pp. 1–7.
[29]. P. B. Rao, D. V. Prasad, C. P. Kumar, Feature extraction using zernike moments, *Int. J. Latest Trends Eng. Technol.*, Vol. 2, No. 2, 2013, pp. 228–234.
[30]. S. X. Liao, Image Analysis by Moments, *Ph. D. Thesis, University of Mantioba*, Canada, 1993, pp. 1-149.
[31]. B. L. Titzer, D. K. Lee, J. Palsberg, Avrora: Scalable sensor network simulation with precise timing, in *Proceedings of the Fourth International Symposium on Information Processing in Sensor Networks (IPSN'05)*, 2005, pp. 477–482.
[32]. M. Vorobyov, Shape Classification Using Zernike Moments, *Semantic Scholar*, 2011, pp. 1–22.
[33]. C. Pham, Communication performances of IEEE 802.15. Four wireless sensor motes for data-intensive applications: A comparison of WaspMote, Arduino MEGA, TelosB, MicaZ and iMote2 for image surveillance, *J. Netw. Comput. Appl.*, Vol. 46, 2014, pp. 48–59.
[34]. B. Oluleye, A. Leisa, J. Leng, D. Dean, Zernike Moments and Genetic Algorithm : Tutorial and Application, *British Journal of Mathematics* and *Computer Science*, Vol. 4, No. 15, 2014, pp. 2217–2236.



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