Object Segmentation Using Block Based Patterns

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***Abstract*—Segmenting homogeneous regions or objects in an image are very much demanding but challenging. *Pattern based object segmentation using split and merge* (PSM) was proposed to overcome the problems of basic *split and merge* (SM) algorithm, which is unable to segment properly all types of objects in an image due to huge variations among the objects in size, shape, intensity and orientation. Though the PSM algorithm has better performance than some other image segmentation algorithms, it is completely unable to segment the connected regions in an image and also has higher rate of shape distortion. Addressing these issues, a new algorithm namely *object segmentation using block based patterns* (OSP) is proposed in this paper considering multi stage merging technique. Experimental results show that the OSP algorithm is not only capable of segmenting connected regions in an image but also yield quite low shape distortion of the regions.** *(Abstract)*

Keywords-Image segmentation; split-and-merge; region stability; pattern matching; micro-blocks; video coding (key words)

I. INTRODUCTION

Image processing has a wide range of practical applications, such as car assembly, robot vision, airport security, object recognition, criminal investigation, and medical image analysis for robotic doctor [1]. Image segmentation is an image processing technique to separate mutually exclusive homogeneous regions of interest of an image. Segmenting objects in an image plays a fundamental role in the field of image processing and image analysis. Segmenting objects in an image is a very difficult and challenging task due to huge number of objects and the variations among the objects in terms of color, intensity and locations.

Many algorithms and techniques for segmenting objects in an image exist in the literature [1]-[7]. Those algorithms and techniques can roughly be categorized into two categories: (i) Boundary-based methods and (ii) Region-based methods. In boundary-based methods, an object is segmented by utilizing the discontinuity of pixel intensity in an image and tends to partition an image by detecting isolated points, lines and edges according to abrupt changes. Region-based methods include the techniques of clustering, region growing, and regions splitting and merging. These algorithms exploit the homogeneity of spatially dense information such as intensity, color, texture etc.

Boundary based algorithms given in [2]-[3] are not efficient due to following reasons: (i) these algorithms do not exploit spatial information, (ii) these algorithms are domain dependent, (iii) thresholds used in these algorithms are manually set, (iv) two adjacent regions do not share the same boundary information in these algorithms.

Region-based algorithms proposed in [4]-[6] are much more efficient than the boundary-based algorithms. S*plit-and-merge* (SM) of [6] is a popular, easy, and simple region-based algorithm to segment objects in an image. In the *split-and-merge* algorithm the foreground of an image is first splitted into smaller regions based on some threshold values manually set for measuring the homogeneity. Identical regions are found with respect to some other threshold values set for measuring the homogeneity. Those identical regions are finally merged to get the final result. Both the splitting and merging are done based on manually specified thresholds, which might not be the optimum values. SM segmentation algorithms are not able to segment all types of objects in an image perfectly. For example, large images with a small number of objects can be effectively segmented by a SM algorithm while the number of objects increases the same algorithm performs poor.

To overcome the problem associated with Basic SM algorithm and its several variations a new algorithm called *pattern based object segmentation using Split-and-Merge (PSM*) was proposed in [7]. This algorithm used the basic concept of the SM algorithm and pattern matching technique. PSM algorithm is also the first image segmentation algorithm that used pattern matching for object extraction. Pattern matching is not a new idea; it is very much familiar in low bit rate video coding [8]-[9]. In this technique, $n \times n$ micro-blocks (MB) are used for motion estimation (ME), where n can be 16, 8, or 4. Though the bigger sized MBs require small number of blocks to compare small sized MBs are preferred to get better results [8]-[9]. Similar block matching concept is applied in the PSM algorithm. In PSM pattern matching concept is integrated in the framework of split and merge algorithm for segmenting objects in an image. However, the

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biggest drawback of PSM algorithm is that it cannot segment the homogeneous regions that are connected. In this paper, we propose a new algorithm *object segmentation using block based patterns* (OSP) taking into account the basic SM algorithm, image feature stability, inter- and intra-object variability and human visual perception. In our OSP algorithm image feature stability is used for splitting the object. Pattern matching technique is used for extracting the foreground of the image from the background and encoding the image. Finally image feature stability, inter- and intra- region variability and human visual perception are considered for merging the segmented regions to get the final segments.

The experimental analysis has been conducted on gray-scale images considering the intensity of pixel as the feature for segmentation. The results of the OSP algorithm are compared with that of the PSM algorithm [7], basic SM algorithm [6], classical fuzzy clustering algorithm namely suppressed fuzzy c-means (SFCM) using combination of pixel intensity and pixel location as the feature for segmentation process [10], and the newly developed shape based clustering algorithm called *object based image segmentation using fuzzy clustering* (OSF) [1]. Our OSP algorithm performs better than all the algorithms mentioned above in segmenting connected regions and producing less distortion.

The rest of the paper is organized as follows: the basic SM algorithm and the supporting literature containing the theorems applied to propose OSP algorithm is detailed in Section II, while the proposed OSP algorithm is presented in Section III. The experimental results are described in Section IV and finally some concluding remarks are provided in Section V.

II. SUPPORTING LITERATURE

In this section, we describe related research works those are directly used to propose our object segmentation algorithm called *object segmentation using block based patterns* (OSP).

A. The Split and Merge (SM) Algorithm

The *split-and-merge* (SM) algorithm, developed by Pavilidis [6], [11] in 1974, is still one of the most popular classical image segmentation algorithms and is widely used directly or indirectly in image processing. In order to understand SM algorithm, let R represent the entire image having different objects. Segmentation may be viewed as a process that partitions R into *n* sub-regions, $R_1, R_2, \ldots, R_n$. Details and summarized steps of SM algorithm are given in [7].

B. Region Stability

Region stability test is applied in both the split and merge stage. A region is said to be stable if it does not contain portion of more than one object. Region stability is measured depending on whether all the samples in a sample space (here, pixels in a region) belong to the same sample space (here, the same region) or not. If the regions are unstable, they are subdivided into several smaller regions or sample spaces. There are many theorems to identify region stability such as Z-test, T-test and Chi-square-test [14]. In this paper, T-test has been applied because of its world wide appeal. In T-test, $Z\%$ fiducial limit is computed as $\bar{X} + tSE$ for large sample space (more than 30 samples), where $\bar{X}$ is the mean of the samples, *SE* is the standard error of mean, and *t* is the value of *t-distribution. SE* and *t* can be calculated by equation (1) and (2) respectively.

$$SE = \frac{\sigma}{\sqrt{n}} \tag{1}$$

$$t_{1-z/100} = \frac{\bar{X}-\mu}{S}\sqrt{n} \tag{2}$$

Where, μ= mean of the population, σ = standard deviation of the population, S = standard deviation of the sample, and n = size of the sample. A region is said $Z\%$ stable, if $-t_{1-z/100} \le t \le t_{1-z/100}$.

C. Segmentation using patterns

Patterns were first successfully used in [8]-[9] to find motion vectors of the objects (micro blocks) in video encoding. A video frame is segmented into one or more moving object using 16×16 blocks, called micro-blocks (MBs). *Wong et. al* [15] compare each micro-block with the patterns P_1-P_8 of Figure 1 to find whether there is any moving object in the micro-block under consideration. A match with any pattern indicates a moving object's presence in the micro-block. Research works in [8]-[9] extended the number of patterns and a complete 32 *pattern codebook (PC)* is proposed which also includes previously mentioned 8 patterns.

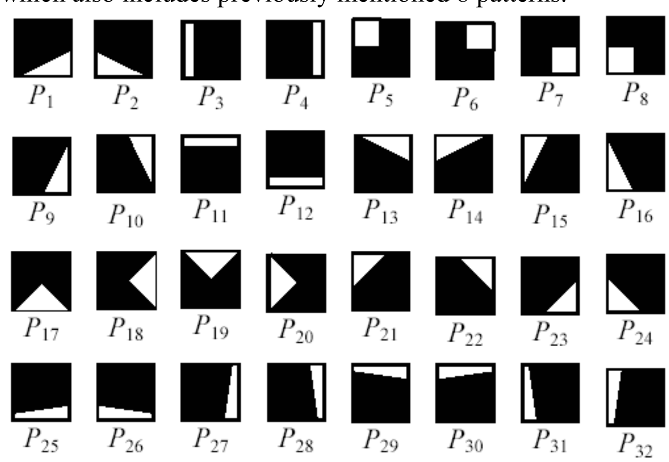


Figure 1: The pattern codebook of 32 regular shaped, 64- pixel patterns, defined in 16×16 blocks, where the white region represents 1 (motion) and black region represents 0 (no motion).

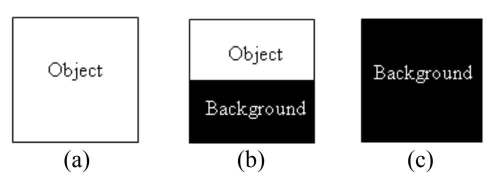


Figure 2: Different types of patterns: (a) Object in the whole pattern (Active MB), (b) the pattern containing both object and background (Active region MB), and (c) the pattern containing only background (Static MB).

The full set of 32 pattern codebook is shown in Figure 1. Based on the results of pattern matching, *Wong et. al.* [15]

classified the micro-blocks into three categories: 1) S*tatic MB* (SMB): MBs that contain little or no motion; 2) *Active MB* (AMB): MBs which contain moving object(s) with little static background; and 3) *Active-Region MB* (RMB): MBs that contain both static background and part(s) of moving object(s). Those regions are shown in Figure 2.

D. *Multistage Merging Technique*

A single criterion for the complete segmentation process causes a dissatisfactory segmentation results. This has motivated Faruquzzaman et. Al. [12] and Brox et. Al. [13] to use a multi-stage approach in which a criterion is used as long as it can well handle the current configuration. Then the criterion is replaced by another one. They have used T-test for both splitting and merging. They also considered intra-region variance minimization and inter-region variance maximization throughout the merging process to maintain object identity. The technique of human visual perception limitation was used to maintain the realistic shape of the identified object.

E. *Intra-variance and Inter-variance Test*

Merging regions using only T-test may not give satisfactory result. This may produce more number of regions than the number of objects in an image. Another merging stage called Intra-variance and Inter-variance Test can optimize the number of regions. The optimal result tends to minimize intra-region variability and maximize inter region variability [12]. To minimize the intra-region variability, the sum of squared error criterion is used such that it fits better to the model. Further, it implements the joint intra-region variability constraint as a minimum variance for the union of two clusters. At the same time, joining two clusters maximizes the inter cluster variability. This leads to the following region growing model:

$$\min_R \sum_{R_i \in R} |n_i| Var(R_i) \tag{3}$$

Where n_i is the number of pixels in region i, $Var(R_i)$ is the variance of the region i

$$Var(Y) = \frac{1}{Y} \sum \|x - \mu(Y)\|^2 \tag{4}$$

Subject to:

$$\forall R_i, R_j, i \neq j;$$

$$MaxVar\left(R - \{R_i, R_j\} \cup (R_i \cap R_j)\right) < MaxVar(R)$$

Where $MaxVar(R) = Var\left(Var(R_k)\right) \forall R_k \in R$

F. *Concept of Human Visual Perception*

If the change of any object or feature is less than or equal to 0.5dB, human perception is unable to detect the change [17]. Now, let the larger region be R_l and the smaller region be R_s. Presence of R_s co-located to R_l creates distortion. The regions R_s will be merged with R_l if they satisfy the following equation:

$$0.5 = 20 \log \frac{R_l}{R_s} \rightarrow 10^{\left(\frac{0.5}{20}\right)} = \frac{R_l}{R_s} \rightarrow 1.059 = \frac{R_l}{R_s}$$

$$\rightarrow R_l = 1.059 R_s \tag{5}$$

Equation (5) has been developed using the fact that for any two neighboring regions, if the size of one region is less than or equal to 6% of another one, human perception cannot differentiate these two regions.

III. PROPOSED MODEL

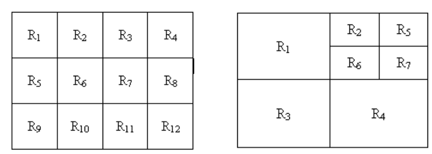
This section presents a new algorithm for image segmentation, namely *object segmentation using block based patterns* (OSP), which is developed to overcome the various segmentation faults of the PSM algorithm. Our proposed OSP algorithm is divided into following stages (i) split stage, (ii) region accepting stage, and (iii) merge stage. The basic assumptions for the OSP algorithm are as follows: (i) the aspect ratio of the image is 1.33 or 4/3 with the image size 1024×768, (ii) the image is segmented into square regions in sizes 16×16 blocks, and (iii) only the foreground pixels are segmented and the back ground pixels are set to zero.

A. *Split Stage*

An image is divided in the split stage in two steps: (i) Split Stage - 1, and (ii) Split Stage - 2. The region stability test is applied in both steps to decide whether the region is stable or not.

1) Split Stage – 1: In this stage, T-test is applied first on the original image of size 1024×768. If the image is found unstable it is subdivided into 12 equal and square sub-regions, which is shown in Figure 3(a).

2) Split Stage – 2: After the completion of split stage-1 split stage-2 is applied. In this stage each square region is recursively subdivided into 4 sub-regions by applying the T-test.



(a) (b)

Figure 3: Split stage of OSP: (a) Split Stage-1, (b) Split Stage-2.

After completing the split stage, the regions are matched with the patterns called micro-blocks (MBs) in region accepting stage.

B. *Region Accepting Stage*

In the split stage, the square regions of different length are produced $R_1, R_2, R_{3,\ldots,} R_n$ where n is the number of the splitted regions. The splitted regions are matched with the patterns of the pattern codebook described in Section C. We use the technique of pattern matching from [7]. If the size of the MB is $a \times b$, the percentage of matching of a region R_i with any pattern P_j can be calculated using the following equation:

$$POM\ (\%) = \frac{\sum_{x=1}^{a} \sum_{y=1}^{b} f(x,y)}{a \times b} \tag{6}$$

Where

$$f(x,y) = \begin{cases} 1; & ImageR_i(x,y) \neq 0 \cap P_j(x,y) = 1, \forall i,j \\ 0; & otherwise \end{cases}$$

If $POM\ (\%) \geq 95$ the pattern P_j is said fully matched with the region R_i. If $60 \leq POM\ (\%) < 95$ the region is said to be partially-matched with the pattern P_j and if POM (%) < 60, pattern P_j is unmatched with the region R_i.

Region accepting stage find three types of regions: accepted region, partially acted region, and rejected region. Accepted region is the region that contains only foreground pixels while partially accepted region has pixels of both foreground and background. The partially accepted regions need to be replaced by the best match pattern and after replacing it will be treated as an accepted region. The rejected region is the background of the image and is not being replaced by a matched pattern. Region accepting stage uses following two steps to mark accepted region and not accepted region:

Step-1 If a region has size greater than the size (16×16) of a micro-block and does not contain any background pixels, then the region is marked as accepted, otherwise, it is marked as rejected.

Step-2 When a region size is equal to the size of the MB, then the regions may be accepted or partially accepted or rejected. If the region does not have any background pixels, it would be treated as accepted region while the rejected block contains only background pixels. On other hand, a region having both background and foreground pixels, is considered as the partially accepted region and in this case, it need to match this region with the given patterns. This region will be replaced by the best match pattern and then this replaced block will be treated as the accepted region. This process will continue for all the regions whose size is equal to that of the MB.

Two regions are selected for merging using multistage merging technique if they are connected and accepted. The merging stage is detailed in the following section.

C. *Merge Stage*

In the merge stage of our OSP algorithm only connected and accepted regions are considered to be merged. Since the single stage merging technique does not give us satisfactory result, multistage merging technique is applied in OSP as discussed in Section D. The merge stage of our proposed OSP algorithm contains three main constituent parts which are applied only on the accepted and connected regions. These are: (i) merging on the basis of T-test, (ii) merging for inter–variance maximization and intra-variance minimization, and (iii) merging regions considering human perception. Details of this merge stage are discussed as follows:

1) *Merging on the basis of T-test:* Some of the regions may be splitted due to the hard partitioning technique in the split stage, though they are the parts of the same object. Any two connected regions are qualified to be merged if they are both stable. These two regions are merged if they are within the 99% fiducial limit of T-test. A region is chosen to merge with another region if they have the minimum combined variance. This process will continue until there is a region that satisfies the merging criteria. The regions obtained after completing the merge on the basis of T-test are stable in nature. They may either be a full object or be a stable part of an object. To merge the stable components of an object another technique is applied which is detailed in the next section.

2) *Merging for Inter-variance Maximization and Intra-variance Minimization:* As mentioned above, there may remain some stable regions, each of which are composed of pixels representing any stable part of an object. As there exists a huge number of objects having different variations among them, these objects are only differentiable if they have different appearance and visually distinct from each other. Since the number of clusters is neither fixed nor manually provided, the minimization of the intra-region variability and the maximization of the inter-region variability in the union of two regions are considered in our algorithm like [16]. However, both the straight minimization of the intra-region variability and the maximization of the inter-region variability lead to undesirable trivial solutions being N regions or 1 region respectively. OSP minimizes the intra- region variability while at the same time constraining the inter region variability in the union of two regions. The reason behind such condition is – if two regions belong to single object, their intensities should be similar and as a result their combined variability should be minimal. On the other hand, when one of nearly intensified region disappears due to merging, the verity of variance is increased while the number of the regions is decreased. This leads to maximization of inter-region variability. Thereby, in the overall image, the inter-variance of object is maximal as they are distinctive from each others. This idea is applied on the remaining regions that need to be merged. This task terminates when no more region can be merged under this criteria.

3) *Merging regions considering human perception:* Even though the splitted regions are merged applying T-test first and then inter- and intra-variance, this may produce some parts of an object as a separate region and hence motivated to consider the human perception for merging as the final merging step. Form the theory it has been seen that, if the change of any object or feature is less than or equal to 0.5dB, then human perception is unable to detect the change [17]. Considering the change of size in light of the above theorem it can be stated that, when any two connected regions are found where the size of any one object is less than or equal to 6% of other, then these two regions are merged to form a single region as a segmented object. This concept is applied at the last step of merging to merge smaller stable regions with their neighboring connected larger region to avoid hedge on the boundary of the identified objects. This gives better shape and look of identified objects.

D. *The OSP Algorithm*

The pseudo code of proposed OSP algorithm is given in **Algorithm 1**. To represent the algorithm formally let us assume the image (R) is defined by a set of regions $R = \{R_1, R_2, \dots, R_n\}$ where $n > 0$ and each region R_i contains a set of pixels whose pixel intensity is defined in set X_i, where $X_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}$ where $d > 0$, μ_i is the average pixel intensity of region R_i. $Connected(R_i, R_j) = 1$ if the region R_i and R_j are connected.

Algorithm 1: *Object Segmentation using block based patterns (OSP) algorithm.*

Inputs: Image, Patterns
Outputs: Final Segmented Regions

1. Resize image to 1024×768.
2. IF *Image* is unstable using T-test, split *Image* into 12 equal regions (Section 4.2).
3. Recursively split region R_i into four equal regions if it is unstable using T-test, $\forall i$.
4. Construct R_{map} having the size of the image
5. FOR each region R_i
   5.1. IF the length of R_i $\neq$ the length of MB, THEN
      5.1.1. IF $\mu_i > 0$, THEN $Accepted(i) = 1$
      5.1.2. ELSE
         $Accepted(i) = 0$
         Set 0 to all the pixels in R_{map} whose region number is *i*.
   5.2. ELSE
      5.2.1. Find the best matched pattern P_i, where $1 \leq j \leq 32$.
      5.2.2. IF the pattern P_i is accepted, THEN
         $Accepted(j) = 1$
         Set 0 to all the pixels in R_{map} whose pixel intensity is equal to the background (0).
         5.2.2.1. ELSE IF the pattern is partially-accepted, THEN
         Replace all the pixels in R_{map} whose value is *i* with the best matched pattern and replace 1 with *i*.
         $Accepted(i) = 1$
      5.2.3. ELSE
         $Accepted(i) = 0$
         Set 0 to all the pixels in R_{map} whose region number is *i*.
6. FLAG = TRUE
7. While FLAG = TRUE
   7.1. FLAG = FALSE
   7.2. FOR each region R_i
      7.2.1. j = region number having minimum weighted combined variance connected to i.
      7.2.2. IF
         $Connected(R_i, R_j) = 1$ and $Accepted(R_i) = 1$ and $Accepted(R_j) = 1$ THEN
         7.2.2.1. IF $T\_test(R_i, R_j) = TRUE$ THEN
            Merge R_i with R_j
            FLAG = TRUE
8. $MaxVar$ = variance of individual region's variance
9. FLAG = TRUE
10. While FLAG = TRUE
   10.1. FLAG = FALSE
   10.2. FOR each remaining region R_i
      10.2.1. j = region number having minimum weighted combined variance connected to i.
      10.2.2. IF
         $Connected(R_i, R_j) = 1$ and $Accepted(R_i) = 1$ and $Accepted(R_j) = 1$ THEN
         10.2.2.1. IF merging R_i with R_j increase the $MaxVar$ value THEN
            Merge R_i with R_j
            FLAG = TRUE
            Update $MaxVar$
11. FLAG = TRUE
12. While FLAG = TRUE
   12.1. FLAG = FALSE
   12.2. FOR each remaining region R_i
      12.2.1. j = all region connected to i.
      12.2.2. IF
         $Connected(R_i, R_j) = 1$ and $Accepted(R_i) = 1$ and $Accepted(R_j) = 1$ THEN
         12.2.2.1. IF ($|R_i| \sim 0.06 * |R_j|$) THEN
            Merge R_i with R_j
            FLAG = TRUE

In this algorithm, firstly the image is resized (Step 1) and then split into 12 equal regions using t-test in Step 2. Then the image is recursively splitted into four regions, if the regions are seemed to be unstable using t-test and then R_{map} is constructed in Step 4. Algorithm finds out the accepted, partially accepted, and rejected regions in Step 5. Merging stage begin from the stage 6. In stage 7 we merge two regions if they proved to be stable by applying T-test. In step 8, 9 and 10 two regions are merged by applying intra-variance and inter-variance test. Remaining regions are merged by applying human visual perception in step 11 and 12.

IV. EXPERIMENTAL RESULTS

Several practical experiments are conducted to verify our proposed OSP algorithm. The results obtained from our OSP algorithm are compared with the result of OSF [1], ROSSM [12] and PSM [7] algorithms. The OSF [1], ROSSM [12], PSM [7] and our proposed OSP algorithms are implemented using MATLAB 7.1. These algorithms are applied to several grayscale images ranges from natural and medical images having different orientations. Some of these experimental results are shown in Figure 4. The performance of our proposed OSP algorithm is quite good for different variations of images. Segmented objects found from the different algorithms are shown along with the original images in Figure 4. Segmented objects produced by the OSF algorithm are shown in Figure 4(b). These objects have small amount of error though the shape of the objects is quite acceptable. Result from ROSSM algorithm is shown in Figure 4(c). Connected objects have been segmented producing good shape and minimum error. However, the running time of

ROSSM algorithm is very high because this algorithm split images near to the pixel level. The segmented objects from PSM algorithm are shown in Figure 4(d). It is clearly shown that this algorithm cannot segment connected objects while the OSP algorithm (shown in Figure 4(e)) can efficiently segment connected objects in an image with a very low running time compared to ROSSM algorithm due to considering connectivity, inter- and intra-variance, and human visual perception. This is proves the superior segmentation performance of the OSP algorithm over other algorithms considered in this paper.

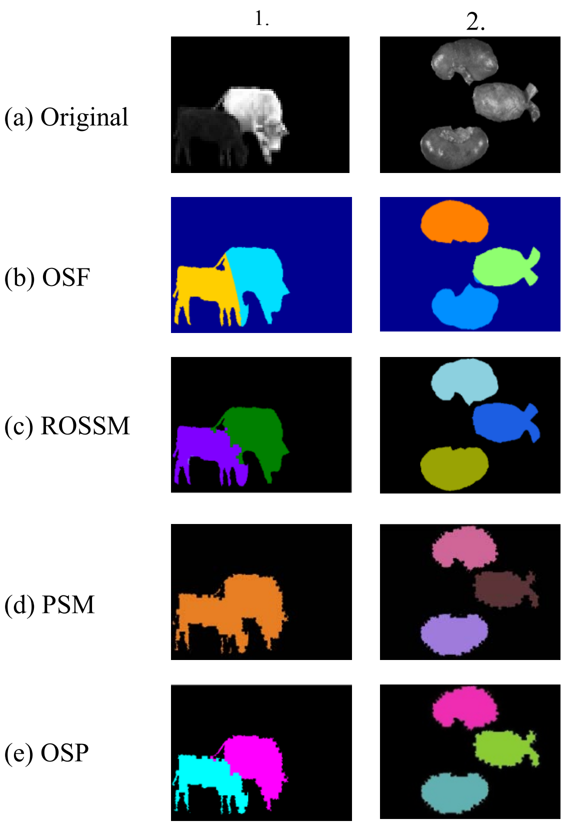


Figure 4: (a) Original Image (b)-(d) Segmentation results of (a) using SFCM for intensity and location, OSF and PSM respectively.

V. CONCLUSION

This paper has proposed a new segmentation approach called *object segmentation using block based patterns* (OSP) to address some of the limitations inherent with the PSM algorithm. The OSP algorithm as like PSM [7] algorithm firstly splits the image into several regions until the region stability is achieved or the block size becomes 16×16. Then the splitted regions are matched with the micro-block (MBs) to produce accepted and rejected regions. Then the accepted and connected splitted regions are merged using multistage merging technique such as T-test, intra-variance and inter-variance test and human visual perception techniques are applied in the time of merging two regions. Experimental results have shown that the newly developed OSP algorithm has been able to segment connected images well and outperforms the *pattern based object segmentation using split and merge* (PSM) [7], *object based image segmentation using fuzzy clustering* (OSF) [1] and *Robust Image Segmentation Based on Split and Merge* (ROSSM) [12]. This will be highly applicable in low bit rate video coding applications for real life application where some misclassification error is acceptable. A little shape distortion occurs due to pattern matching in 16×16 size regions in OSP algorithm. In the future research work, we will improve the efficiency of the OSP algorithm by reducing the shape distortion of the segmented objects.

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