Journal of Scientific Research and Advances

ISSN 2395-0226

DETECTING COMPLEX IMAGE DATA USING MODIFED SURF

Imran khan[1], Deepak Kumar Singh[2]
[1] Dept. of Information Technology, ITM Gwalior, Uttar Pradesh, *Imrankhan0611@gmail.com*
[2] Dept. of Computer Science, CSE College Jhansi, Uttar Pradesh, deepakk005@gmail.com

A real-time fully autonomous system becomes robust for a security and surveillance system today. In this research, a moving camera is presented to track a dynamic scene that is a complex image for real-time object detection using a robust approach. The improved SURF algorithm is used for the detection of the moving object and the tracking of the detected object. The improved SURF algorithm with feature detection technique includes a color feature also to achieve a more accurate and robust results. This approach is able to track the detected object while re-entering the scene after being absent for a short period of 4 or 5 frames. The results are compared for speed and accuracy in the regular SURF, MSER, enhanced SURF, and the current approach.

Keywords: Complex Image, Feature Detection, MSER, SURF Algorithm, MATLAB

I. INTRODUCTION

The name ‘data mining’ derives from the metaphor of data as something that is large, contains far too much detail to be used as it is, but contains nuggets of useful information that can have value. So data mining can be defined as the extraction of the valuable information and action able knowledge that is implicit in large amounts of data. The data used for customer relationship management and other commercial applications is, in a sense, quite simple. A customer did or did not purchase a particular product, make a phone call, or visit a web page. There is no ambiguity about a value associated with a particular person, object, or transaction.

It is also usually true in commercial applications that a particular kind of value associated to a customer or transaction, which we call an attribute, plays a similar role in understanding every customer. For example, the amount that a customer paid for whatever was purchased in a single trip to a store can be interpreted in a similar way for every customer – we can be fairly certain that each customer wished that the amount had been smaller.

In contrast, the data collected in scientific, engineering, medical, social, and economic settings is usually more difficult to work with. The values that are recorded in the data are often a synthesis of many underlying processes, that mixed together in complex ways, and sometimes overlaid with noise. The connection between a particular attribute and the structures that might lead to actionable knowledge is also typically more complicated. The kinds of mainstream data-mining techniques that have been successful in commercial applications are less effective in these more complex settings. Matrix decompositions, the subject of this book, are a family of more-powerful techniques that can be applied to analyze complex forms of data, sometimes by themselves and sometimes as precursors to other data-mining techniques.

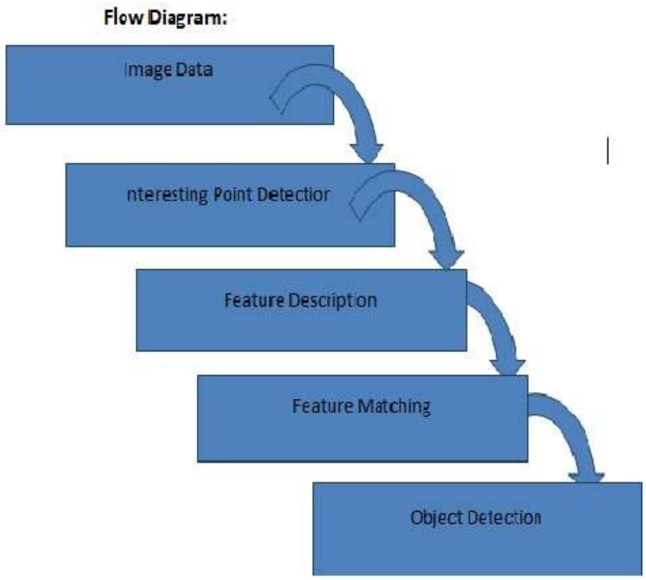
II. DESCRIPTION OF THE ALGORITHM

Comparison with linear scale-space representation while not being used explicitly in SURF, we take interest here in the approximation of Gaussian kernels by box filters to understand the advantages and the limitations of the SURF approach.

This algorithm includes following steps:

1. Read Image and Detect Feature Points.
2. Extract Feature Descriptors
3. Find Putative Point Matches
4. Locate the Object in the target Using Putative Matches.
5. Display the detected object.

Flow Diagram:-



III. RELATED WORK

Point Detection:

During the detection step, the local maxima in the box-space of the "determinant of Hessian" operator are used to select interest point candidates. These candidates are then validated if the response is above a given threshold. Both scale and location of these point candidates are then refined using quadratic fitting. Typically, a few hundred interest points are detected in a megapixel image.

Algorithm 1
input: image u, integral image U, octave o, level i
output: DoHL(u)
function Determinant_of_Hessian (U; o; i)
L   2oi + 1
for x := 0 to M □ 1, step 2o□1 do (Loop on columns)
for y := 0 to N □ 1, step 2o□1 do (Loop on rows)
DoHL(u)(x; y)
end for
end for
return DoHL(u)
end function

Algorithm 2

input: image u
output: listKeyPoints
(Initialization)
U   IntegralImage(u) (Eq. (1))
(Step 1: filtering of features)
for L do (scale sampling)
DoH^L(u) Determinant_of_Hessian (U; L)
end for
Step 2: selection and refinement of key points
for o := 1 to 4 do (octave sampling)
for i := 2 to 3 do (levels sampling for maxima location)
L -> 2^o i + 1
listKeyPoints -> list Key Points + Key Points(o;
i;DoH^L(u))
end for
end for
return list Key Points

So that the scale normalization factor C(L) for second order box filters should be proportional to 1 L2 However, the previous normalization is only true when L1. Indeed, while we have kDxxGσk2 2 kDxyGσk2 2 = 3 at any scale σ, this is not exactly true with box filters, where: kDL xxk2 2 kDL xyk2 2 = 3(2L−1) 2L ≈ 3 when L1. To account for this difference in normalization for small scales, while keeping the same (fast) un-normalized box filters, the author of SURF introduced in Formula (24) a weight factor: w(L) = kDL xxk2 kDL xyk2 ·kDxyGσk2 kDxxGσk2 =r2L−1 2L . (26) The numerical values of this parameter are listed in the last column of Table 2. As noticed by the authors of SURF, the variable w(L) does not vary so much across scales. This is the resaon why the weighting parameter w in Eq. (10) is fixed to w(3) = 0.9129.

Feature selection:

In our methodology, interest points are defined as local maxima of the aforementioned DoHL operator applied to the image u. These maxima are detected by considering a 3 × 3 × 3 neighborhood, and performing an exhaustive comparison of every voxel of the discrete box-space with its 26 nearest-neighbors. The corresponding feature selection procedure is described in Algorithm 3.

Algorithm 3

Selection of features
input: o,i,DoHL(u) (Determinant of Hessian response at octave o and level i)
output: list Key Points (List of key points in box space with sub-pixel coordinates (x,y,L))
function KeyPoints (o,i,DoHL(u)) L ← 2oi + 1 for x := 0 to M −1,
step 2o−1 do (Loop on columns) for y = 0 to N −1, step 2o−1 do (Loop on rows)
if DoHL(u)(x,y) > tH
Then (Thresholding)
if is Maximum (DoHL(u),x,y)
then (Non-maximum suppression)
if isRefined (DoHL(u),x,y,L)
then addListKeyPoints (x,y,L)

```
end if
 end if
 end if
 end for
end for
 return listKeyPoints
end function
```

Remark A faster method has been proposed in [21] to find the local maxima without exhaustive search, which has been not implemented for the demo.

IV. IMPLEMENTATION AND RESULT ANALYSIS

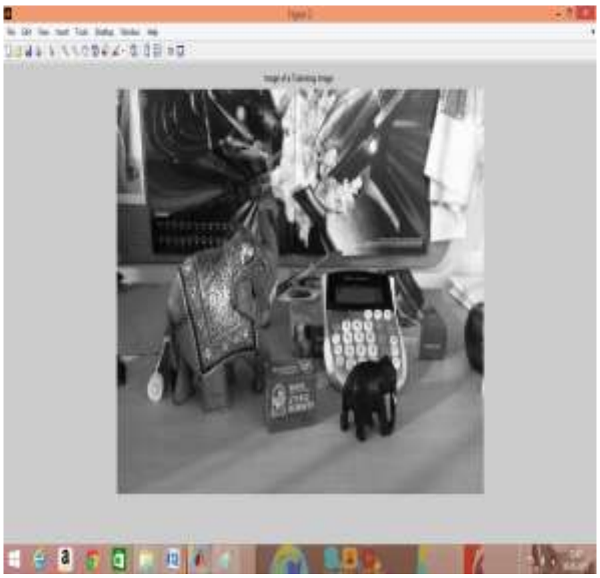


Figure 4.1: Image that will trained

Fig 4.2 : Select feature points from box image

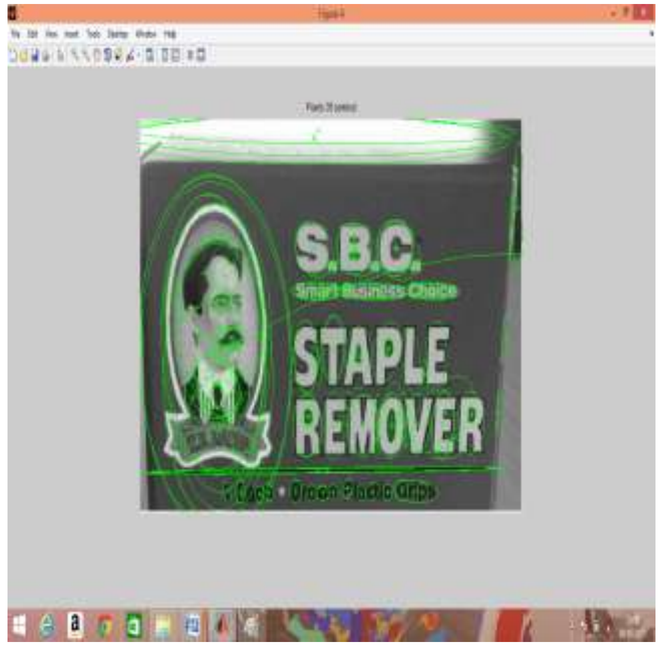


Figure 4.3: calculation of points of centriod of box image

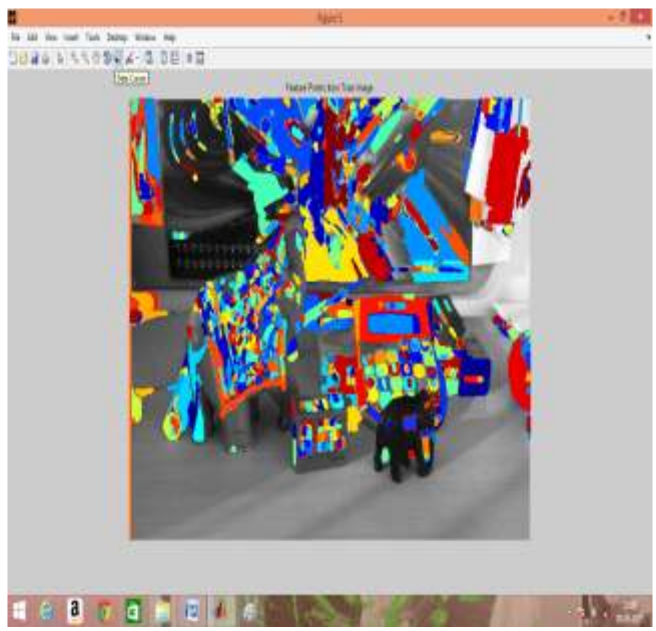


Figure 4.4: detects feature points from trained Image

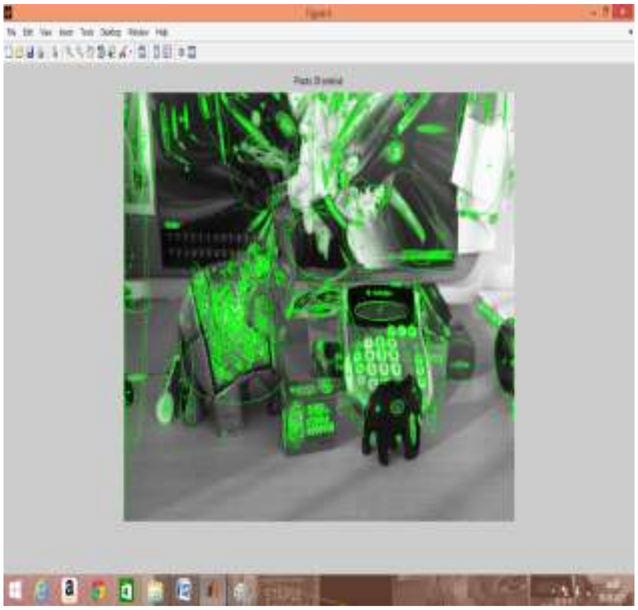


Figure 4.5: calculate centriod points from trained image

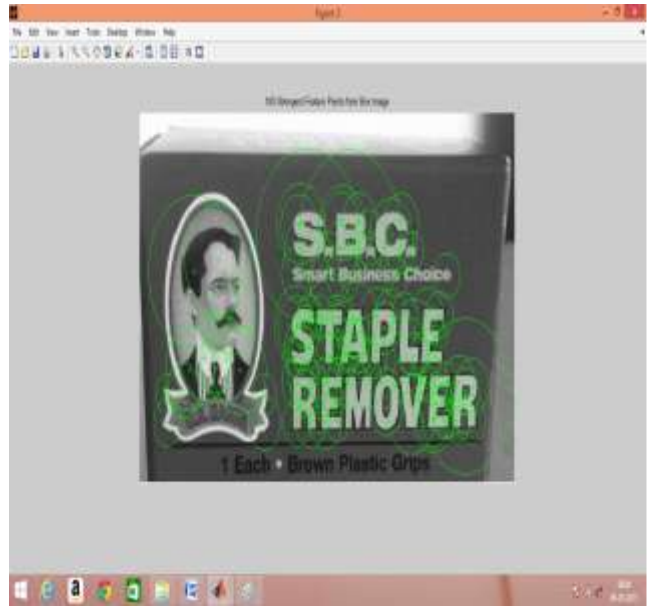


Figure 4.7: feature selection and centriod calculation using MSER Algorithm

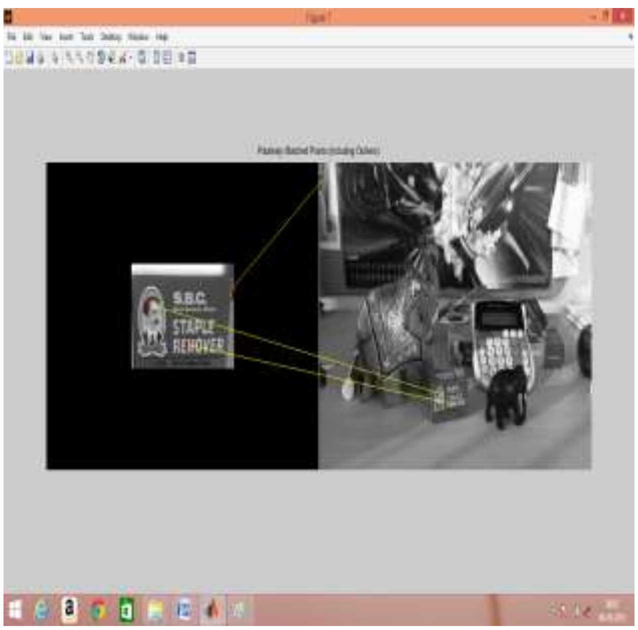


Figure 4.6: relatively detect and matched points outliers are also detected using MSER algorithm

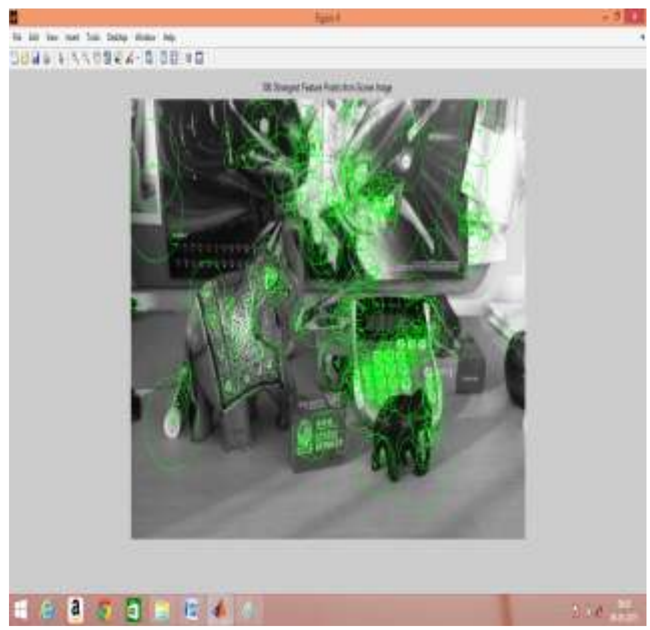


Figure 4.8: Feature point detection using MSER algorithm

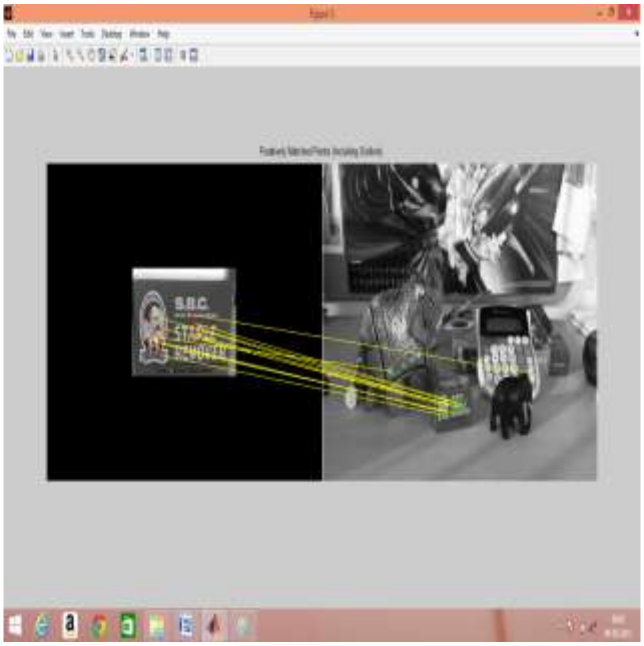


Figure 4.9: Matching of maximum number of points using IMSER algorithm

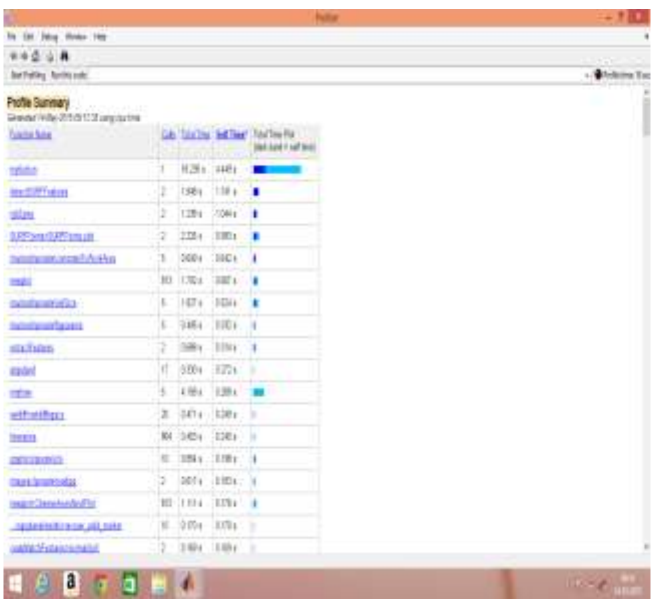
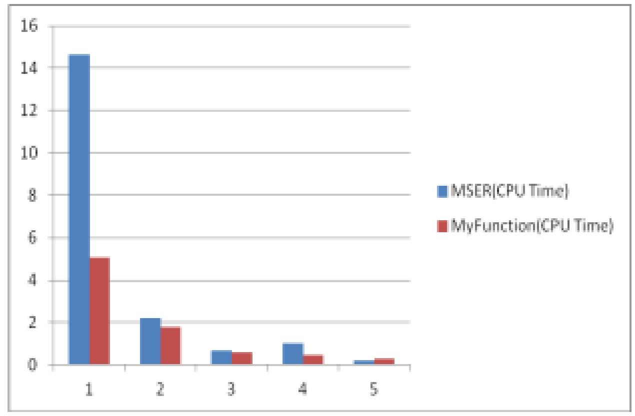


Figure 4.10: the result summary showing the better self time with respect the detection percentage is 33% more than MSER/SURF.

Graph Result:



V. CONCLUSIONS

In this dissertation we have presented the SURF and MSER algorithm for local, compact and invariant representation of natural images. This method achieves state of the art performance in image matching, while being faster than the best competitive methods. Its use is therefore of great interest for computer vision. The numerical performance of the proposed implementation of SURF are consistent with those reported in [2], but also with other implementations of SURF (OPENCV, mat lab). As shown in the experimental section, SURF algorithm is indeed invariant to similarity transform but it also suffers from strong limitations: it is not robust to non-linear contrast change, it suffers from poor and unreliable detections under weak illumination, and it is only usable for small baseline stereo. An interesting extension of this work with my IMSER algorithm we gain 98% detection rate which is 33% more than the MSER and 35% more than the SURF algorithm.

In future we try to gain 100% detection rate adding with DIP techniques.

1.
2.

VI. REFERENCES

[1]. Berg. Shape Matching and Object Recognition. PhD thesis, Compute Science Division, Berkeley, 2005.

[2] V. Ferrari, T. Tuytelaars, and L. Gool. Object Detection by Contour Segment Networks. In an *European Conference on Computer Vision* (ECCV), 2006.

[3] T. Tuytelaars. Dense Interest Points. In *Computer Vision and Pattern Recognition* (CVPR), 2010.

[4] P. Arbelaez, M. Marie, C. Fowlkes, and J. Malik. From Contours to Regions: An Empirical Evaluation. In *Computer Vision and Pattern Recognition* (CVPR), 2009.

[5] D. Hoiem, A. Stein, A. Efros, and M. Hebert. Recovering Occlusion Boundaries from a Single Image. In *International Conference on Computer Vision* (ICCV), 2007.

[6] F. Jurie and C. Schmid. Scale-Invariant Shape Features for Recognition of Object Categories. In *Computer Vision and Pattern Recognition* (CVPR), 2004

[7] P. Gwosdek, S. Grewenig, A. Bruhn, and J. Weickert. Theoretical foundations of Gaussian convolutionbyextendedboxfiltering. Scale Space and Variational Methods in Computer Vision, pages 447–458, 2012. http://dx.doi.org/10.1007/978-3-642-24785-9_38.

[8] J. Matas, O. Chum, M. Urba, and T. Pajdla. Robust Wide Baseline Stereo from Maximally Stable Extremal Regions. In British Machine Vision Conference (BMVC), 2002.

[9] K. Mikolajczyk and C. Schmid. Scale and Affine Invariant Interest Point Detectors *International Journal of Computer Vision*, 1(60):63–86, October 2004.

[10] K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. V. Gool. A Comparison of Affine Region Detectors. *International Journal of Computer Vision*, 65:43–72, 2005.

[12] E. Nowak, F. Jurie, and B. Triggs. Sampling Strategies for Bag-of-Features Image Classification In *European Conference on Computer Vision* (ECCV), 2006.

[13] F. Jurie and C. Schmid. Scale-Invariant Shape Features for Recognition of Object Cate gories In *Computer Vision and Pattern Recognition* (CVPR), 2004.

[14] A. Levin and Y. Weiss. Learning to Combine Bottom-Up and Top-Down Segmentation In *European Conference on Computer Vision* (ECCV), 2006

[15] D. Hoiem, A. Stein, A. Efros, and M. Hebert. Recovering Occlusion Boundaries from a Single Image. In *International Conference on Computer Vision* (ICCV), 2007

[16] D. Comaniciu and P. Meer. Mean Shift: A Robust Approach Toward Feature Space Analysis. IEEE Trans. on Pattern Analysis and Machine Intelligence, 24(5):603–619, 2002.

[17] P. Felzenszwalb and D. Huttenlocher. Efficient Graph-Based Image Segmentation. *International Journal of Computer Vision*, 59(2), 2004.

[18] A. Levinshtein, C. Sminchisescu, and S. Dickinson. Multiscale Symmetric Part Detection and Grouping. In *International Conference on Computer Vision* (ICCV), 2009.

[19] X. Ren, C. Fowlkes, and J. Malik. Figure/Ground Assignment in Natural Images in *European Conference on Computer Vision* (ECCV), 2006.

[20] C. Liu, J. Yuen, A. Torralba, J. Sivic, and W. Freeman. Sift Flow: Dense Correspondences across Different Scenes. In *European Conference on Computer Vision* (ECCV), 2008.

[21] O. Duchenne, A. Joulin, and J. Ponce. A Graph-matching Kernel for Object Categorization. In *International Conference on Computer Vision* (ICCV), 2011.

3.