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THE ROLE OF CONTEXT IN THE VISUAL IDENTIFICATION OF OBJECTS

ULOGA KONTEKSTA U VIZUALNOJ IDENTIFIKACIJI OBJEKTA

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Abstract

The goal of this study was to determine the degree of information needed for humans to attain complete object recognition from a scene, based on the object's local image versus degree of available contextual information. For that purpose, test subjects were *presented* with a series of masked objects, both in and out of context. It was hypothesized that context would strongly influence the ability of test subjects to recognize objects within a scene. A total of 15 object images from three separate image collections were used, which were presented to some subject's in-context and to other subject's out-of-context. There were a total of 10 subjects, and subject selection for the two groups was non-randomized. A total of 5 subjects were presented with in-context images. Each presentation was displayed to the test subject long enough for complete recognition of the object to take place. A slide show was used to present the objects manually, where the automatic image changer was disabled so the image transition could be controlled by the subject. The subject's total exposure time to each image was roughly 30 to 60 seconds, on average. In support of the initial hypothesis, the experiment revealed that the presence of context facilitates object recognition. The results for the experiment can be seen in table 2 and the graphed results can be observed in figure 3. As the data show, there is a strong tendency for contextual clues to assist in the speed and accuracy of object recognition. A dynamic masking capability, allowing for the application of various types of masks to a region of interest (ROI) containing the object could be identified. The system could be explored and expanded widely in order to allowing recognition to be based solely on the degree to which the object under consideration is obscured by its mask.

Key words
Object, visual identification, context, total exposure

Ključne reči
Predmet, vizualna identifikacija, kontekst, potpuno izlaganje

I. INTRODUCTION:

In this study, it was our goal to determine the degree of information necessary for a human to attain complete object recognition from a scene, based on the object's local image and the degree of contextual information available. In order to measure the level of influence that context has on object recognition, we presented test subjects with a series of masked objects, both in and out of context. The portions of the mask then were incrementally removed recording at what point during the unmasking process subjects were able to recognize each object. We hypothesized that context would strongly influence the ability of test subjects to recognize objects within a scene, and our assumption was in line with the prevailing view that context provides numerous clues that aid in the recognition of objects. Accordingly, it anticipated that those objects presented out of context would be less readily identifiable than those presented within scenes. Moreover, the amount of information revealed through the mask at the moment that recognition occurs was anticipated to be less for an object in the context of its natural environment than for an object isolated from its surroundings. Our ultimate goal was to establish a baseline for performance against which a machine-based recognition system could be established. It is our thought that determining whether such a system would benefit from inference based on contextual clues could inform system design, with designers placing more or less emphasis on contextual recognition depending on its usefulness.

II. Procedure:

A total of 15 object images from three separate image collections were used (see section VI for a representative sample of the image set), which were presented to subjects in-context and to other subjects out-of-context. There were a total of 10 subjects, and subject selection for the two groups was non-randomized. A total of 5 subjects were presented with in-context images. A total of 5 subjects were presented with out-of-context images. When presented in context, the objects were in scenes that represented their normal surroundings. For example, in the case of an object such as a lighting fixture, it was presented as part of a living room scene, surrounded by other objects one would expect to see in such a scene. By contrast, when the objects were presented out of context, they were cut out of their original scene and centered against a nondescript gray background. This isolation from surroundings had the effect of removing all contextual clues, as well as those arising from spatial orientation. To again take the case of the lighting fixture, this meant that it was simply "floating" in the middle of a large gray background with nothing to influence subject expectations. Figure 1 shows the lighting fixture object both in and out of context.

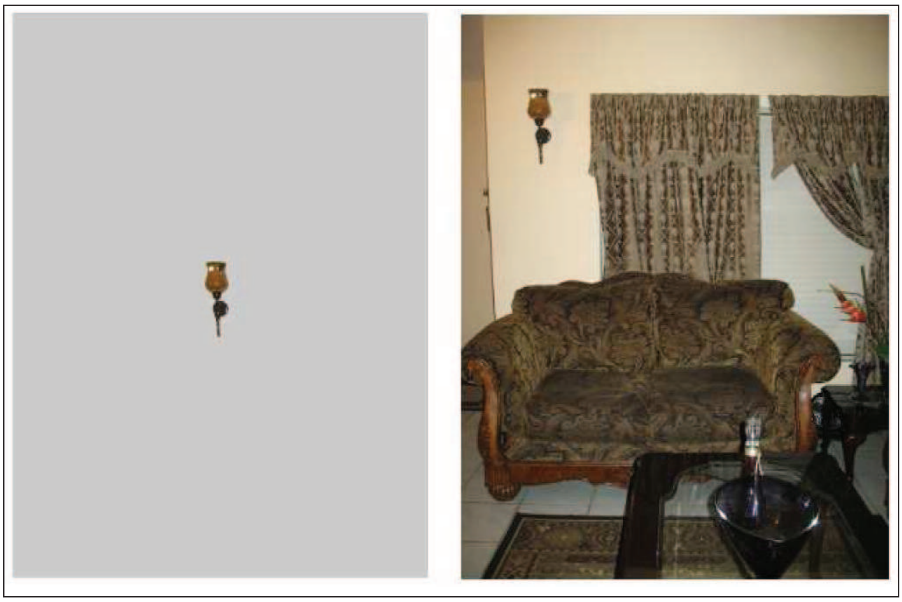

Figure 1 Light Fixcture without context (left) and with context (right)

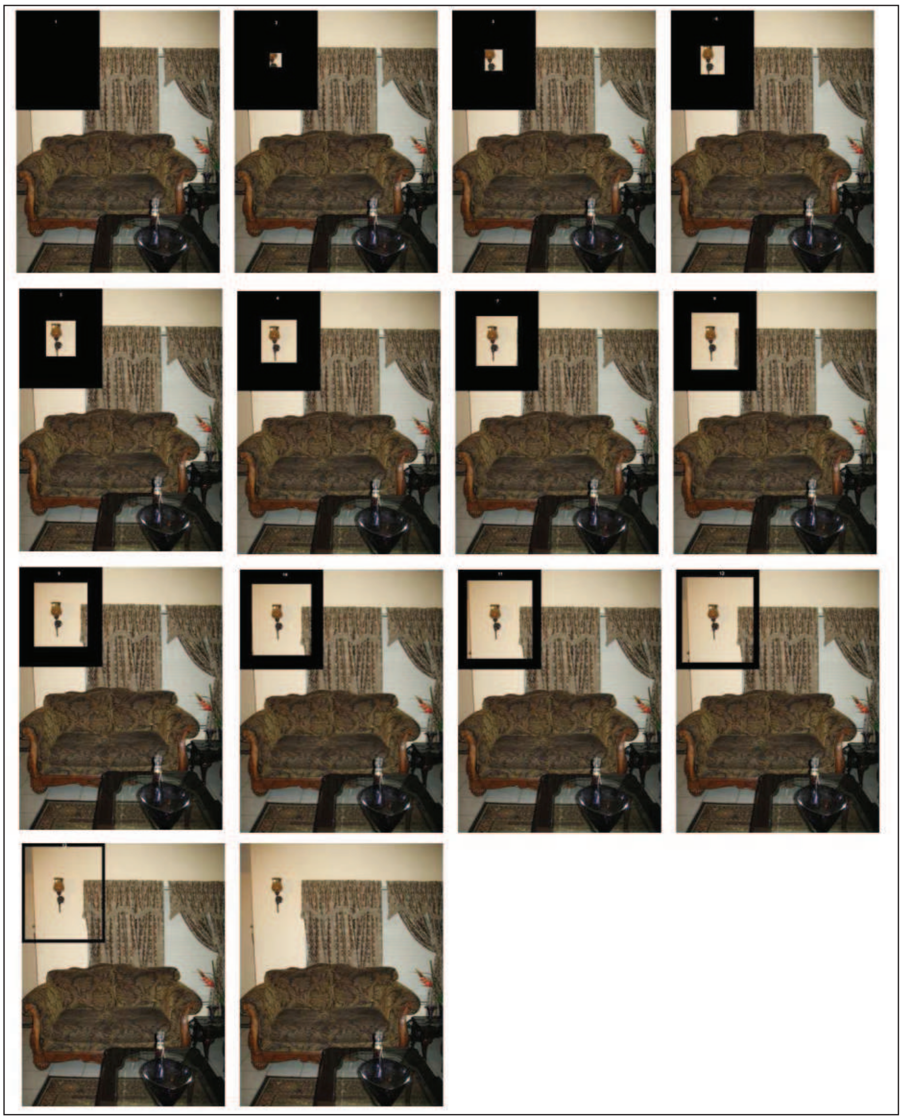

Figure 2 – Light fixture (in context) shown in all stages of unmasking

In both the in-context and out-of-context cases, objects were initially presented behind an opaque black mask, set with a slight blur. This image presentation was the first of a total of fourteen for each object. In each subsequent presentation, a portion of the mask was removed until, by the fourteenth and final presentation, the object was revealed in its entirety. Figure 2 shows the in-context version of the lighting fixture object during all stages of unmasking.

Each presentation was displayed to the test subject long enough for complete recognition of the object to take place. A slide show was used to present the objects manually, where the automatic image changer was disabled so the image transition could be controlled by the subject. The subject's total exposure time to each image was roughly 30 to 60 seconds, on average. Each delivery of the experiment, in its entirety from start to finish, ran approximately 8 to 12 minutes. Note that we do not use exact time figures in each case, because the time required for complete recognition of each object was highly variable among subjects, and the unmasking process could at times become interrupted by either the test subject or test presenter.

When complete object identification occurred, the object presentation number, as well as the name of the recognized object, were recorded by the subject on a data sheet provided for such use (see section VI). The name of each object provided by the subjects was requested to be as exact as possible. After a brief period for documenting the observation, the subject was presented with the next completely masked object and the unmasking process was begun anew. After the experiment, the responses were checked for accuracy of the object name and, in an isolated instance or two, the image was revisited by the subject to check for errors.

Data collected after each presentation included the name of the image, whether it was presented in or out of context, and the presentation number at which it was identified by the subject. Data reflecting these characteristics are presented in section IV of this paper.

III. APPARATUS:

Hardware:

The majority of the images were presented on a Dell Dimension E310 running the Windows XP operating system. The machine contained a Pentium 4 processor and 0.99 GB of RAM. The display used for presentation was a 19” LCD screen set at a resolution of 1280 X 1024. Three experiments were run on Apple computers in the Visual Mind Lab of the Department of Psychology at FAU (Florida Atlantic University). These computers yielded comparable results to those obtained from the Dell.

Software – Image Processing:

Images were manually processed using Adobe Illustrator, Adobe Photoshop, and GIMP (GNU Image Manipulation Program), with the former two used primarily for the application of masks and blurring, and the latter used for removal of objects from their context. The selection of these tools was somewhat arbitrary, arising based on the experimenters’ access to different tools at different times. Regardless of which tool was used in a given stage of image processing, the resulting images were saved in Portable Network Graphics (PNG) format. PNG seemed the obvious choice for file type due to its lossless compression.

Software – Image Presentation:

The majority of the images were presented as part of a slideshow in Microsoft Office Picture Manager. The automatic image-transition feature of the slide show was disabled so that each subject could manually transition between images, taking the necessary time to achieve complete object recognition. Each state of unmasking was presented at an interval of approximately 3-10 seconds. Microsoft Office Picture Manager was chosen for presentation since it readily available and presented the images largely and clearly on the screen. Alternatively, PowerPoint or even MATLAB might have sufficed, but there was no compelling reason for switching to a different piece of software for image presentation. (*The reader is encouraged to consider the use of MATLAB as part of an alternative approach, as outlined in section VI, however*).

IV. EXPERIMENTS:

The image dataset for this experiment was obtained from the image archive of Dr. Elan Barenholtz, Professor of Psychology and director of the Visual Mind Lab at Florida Atlantic University. The images consisted of random collections of various household scenes, and the 15 images chosen for the experiment were selected based on object size, lack of object obscurity or occlusion, and, to a certain extent, the salience of the object within the scene. The two groups of images (the ‘in context’ and the GIMP-created žout of context’) consisted of 15 sets of 14 masked images, yielding a total of 210 images for each group.

The masks were created using Adobe Illustrator’s default “point” system of measurement in its design

Table 1: Conversions from Masking Levels to Percentage of Revelation

Level 1 = (0 Pt x 0 Pt) = 0% Revealed
Level 2 = (35.71 Pt x 42.86 Pt = 1530.53 Pt^2) = 2.04% Revealed
Level 3 = (53.57 Pt x 64.29 Pt = 3444.02 Pt^2) = 4.6% Revealed
Level 4 = (71.43 Pt x 85.71 Pt = 6122.27 Pt^2) = 8.16% Revealed
Level 5 = (89.28 Pt x 107.14 Pt = 9565.46 Pt^2) = 12.75% Revealed
Level 6 = (107.14 Pt x 128.57 Pt = 13774.99 Pt^2) = 18.37% Revealed
Level 7 = (125 Pt x 150 Pt = 18750 Pt2) = 25% Revealed
Level 8 = (142.86 Pt x 171.42 Pt = 24489.06 Pt^2) = 32.65% Revealed
Level 9 = (160.72 Pt x 192.86 Pt = 30996.46 Pt^2) = 41.3% Revealed
Level 10 = (178.57 Pt x 214.28 Pt = 38263.98 Pt^2) = 51% Revealed
Level 11 = (196.39 Pt x 235.71 Pt = 46291.09 Pt^2) = 61.72% Revealed
Level 12 = (214.29 Pt x 257.14 Pt = 55102.53 Pt^2) = 73.47% Revealed
Level 13 = (232.14 Pt x 278.57 Pt = 64667.23 Pt^2) = 86.22% Revealed
Level 14 = (250 x 300 Pt = 75000 Pt2) = 100% Revealed

** Refer to figure 2 for a sample progression of the mask-size levels desktop (1 point = 1 Pt = 0.3528 millimeters). The total mask size was determined by the size of the largest object used in the experimental dataset, which was a chair that fit a rectangular area of roughly 250 Pt X 300 Pt. Given this, the overall area of the black mask was set to 250 Pt X 300 Pt = 75,000 Pt^2, which covered a total of 15.5% of the total 612 Pt X 792 Pt = 484,704 Pt^2 size of the entire image. The size chosen to be revealed in the center of each mask was based on initial increments of integer-Pt values, but, due to an image re-sizing issue, the increment size shifted to decimal-Pt values. The levels of object revelation and the corresponding thresholds of visible information, expressed as percentages, are given in the following set of increments:

NOTE: The percentage of object unmasking/revelation was computed by dividing the area of the central portion of the mask that was revealed by the area of the total mask. For example, at level 2, [(1530.53 Pt^2) ÷ (75000 Pt^2)] × 100% = 2.04%.

Table 2: Results from object with and without Context Experiment

		Objects With Context							Objects Without Context						
		Recognition Level for Each Subject					Average Level of Recognition	Threshold (=Average% Revealed)	Recognition Level for Each Subject					Average Level of Recognition	Threshold (=Average% Revealed)
	Object	S1	S2	S3	S4	S5			S6	S7	S8	S9	S10		
1	Wine Bottle	2	3	2	2	2	2.2	2.6%	3	4	3	2	2	2.8	4.2%
2	Chair	2	14	11	11	5	8.6	47.6%	14	13	14	14	14	13.8	92.2%
3	Computer Monitor	3	7	7	5	7	5.8	18.5%	8	6	6	6	4	6	19.18%
4	Television	9	10	9	4	5	7.4	30.9%	9	10	9	9	8	9	57.13%
5	Fan	2	3	2	2	2	2.2	2.6%	4	4	3	4	2	3.4	6.2%
6	Light Fixture (Sconce)	4	5	3	2	3	3.4	6.4%	5	4	2	3	2	3.2	5.9%
7	Karaoke Machine	7	4	7	10	3	6.2	22.8%	8	7	7	7	6	7	25.2%
8	Microwave	2	5	4	3	2	3.2	5.9%	8	7	5	5	5	6	19.18%
9	Wall Painting	9	3	4	2	2	4	11.6%	4	6	3	4	7	4.8	12.9%
10	Stereo	2	4	3	2	2	2.6	3.8%	6	5	5	5	3	4.8	12.2%
11	Pillow	3	7	5	3	3	4.2	10.3%	7	7	9	8	6	7.4	28.5%
12	Hand Towel	2	3	3	2	3	2.6	3.6%	5	14	3	14	7	8.6	48.5%
13	Model Sailboat	5	4	4	4	3	4	8.4%	4	3	3	4	3	3.4	6.7%
14	Bicycle Tire	3	3	3	3	3	3	4.6%	4	5	5	5	4	4.6	14.3%
15	Brown Bag	5	5	4	3	5	4.4	10.2%	5	6	5	8	4	5.4	16.9%

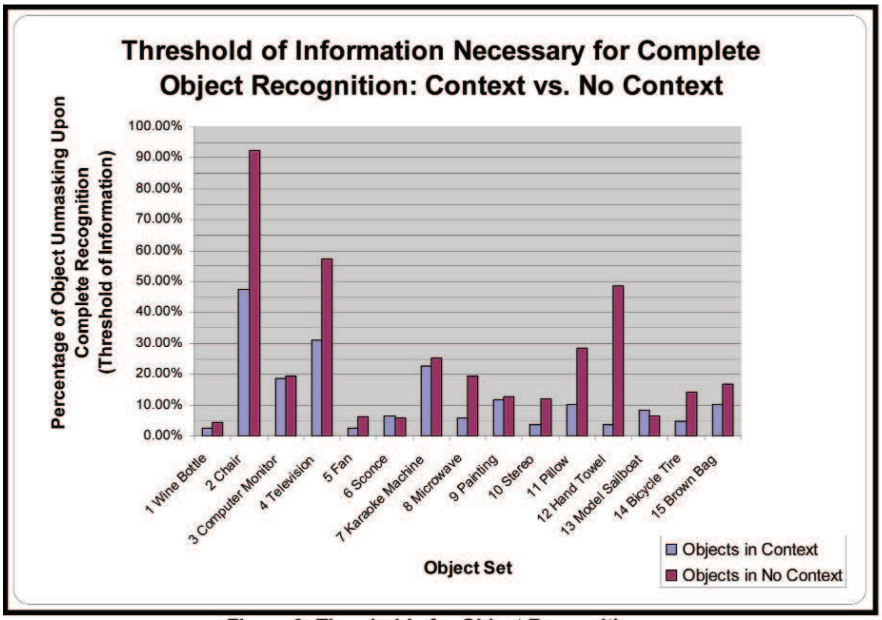

Figure 3: Thresholds for Object Recognition

Each level of masking was labeled with its respective number (i.e., 1st mask = level 1, 2nd mask = level 2, etc.) The masked images were blurred using a ~2.5% Gaussian-Filter within Adobe Photoshop to remove small amounts of unnecessarily apparent detail from certain objects and to provide an additional small amount of object disguise.

After several discussions, it was decided that 10 subjects would be selected for the study. For each subject, instructional data sheets were created and printed, with 5 for the in-context group and 5 for the out-of-context group. Upon beginning each experiment, the subject was presented with the instructions and data sheet, followed by the first image of the 15 total object image sets. Depending on the group, the object was either in a contextual scene or on a neutral, non-contextual background. The initial, fully masked presentation was presented for a brief moment, followed by each successively un-masked presentation for a similar amount of time. Subjects were asked to identify the objects as soon as they became fully recognizable, at which point the image presentation was paused to make a record of the observation. The experiment was run over a number of weeks, and the majority of participants consisted of college students or college-educated adults.

Assumptions:

It was assumed that the subjects had relatively common and past exposure to objects and interior environments to enable them to identify the objects presented. It was also assumed that the subjects were not sufficiently visually, perceptually, or cognitively impaired that it would impact their ability to render a decision in the experiment.

Limitations:

This study did not randomly select subjects for assignment to groups. The study did not control for or take into account the interference of visual or other distractions on subjects that may have impacted their concentration on the task and/or perceptions.

V. EXPERIMENTATION CONCLUSIONS:

In support of the initial hypothesis, the experiment revealed that the presence of context facilitates object recognition. The tabulated results for the experiment can be seen in table 2 and the graphed results can be observed in figure 3. As the data show, there is a strong tendency for contextual clues to assist in the speed and accuracy of object recognition. According to Palmer, "context appears to affect the *efficiency* of categorization" [(1)].

Overall, object recognition in context conditions was clearly more efficient than out of context recognition, however, in two cases, the data show a very subtle inverse relationship between the amounts of context available and the ability to recognize the object [(2)]. In the case of the sconce and the model sailboat, the results indicate that these objects were slightly more recognizable, on average, out of context than in context. Although the discrepancy in the results for the sconce was due to one individual's response, according to the data, the model sailboat (located on a countertop in a kitchen scene) was slightly less subtle. Theoretically, although the images with objects in context did not have truly *misleading* or *inappropriately placed* objects in them, per say, the fact that the sailboat was located as model-ornament on a countertop in a kitchen may have caused the subjects to question the consistency of the object and context. This may have led to the overall larger average of necessary object exposure for complete recognition of the object to occur, given its context.

Some of the more profound results came from objects such as the chair, television, pillow, and hand towel. These objects were particularly well placed in contexts consistent with their object features, such as in the dining room, bedroom, living room, or kitchen area, respectively. Recognition of these objects required the greatest amount of information when out-of-context, indicating a much higher threshold than when in context (3). Overall, the results came out nicely and reflected a reasonably reliable measure of the average threshold of information a human needs to recognize an object.

VI. CONCLUDING RECOMMENDATIONS FOR FURTHER EXPERIMENTATION

An Alternative Approach to Presentation

In this project's early stages, the goals were far more ambitious. It was hoped that in addition to the results detailing subject performance, a reusable MATLAB script could be created, allowing for similar experiments to be conducted in the future with relative ease. While MATLAB seemed like a promising platform for such an application, it needn't be the only platform for consideration. Any technology set able to deliver the desired functionality would be adequate. Optimally, the application should have the following features:

- The ability to accept (e.g., read from a file) a list of images to be presented and their presentation interval as input
- A dynamic masking capability, allowing for the application of various types of masks to a region of interest (ROI) containing the object to be identified. Examples include:
  - A black box of the kind used in this experiment
  - Regular polygonal masks
  - Irregular polygonal masks approximating the size and shape of the masked object
  - Blurring effects obtained through changing resolution or otherwise manipulating the region of interest
- The ability to consume files describing the masks to be applied (e.g. type, location, dimensions)
- A facility for user input, allowing users to halt the presentation process and type (or, perhaps, speak) submit their response without the need for interaction

with the experimenter. Such a facility could itself be configurable, allowing for various response types, including freely typed text, multiple choice, and even voice input.

- The ability to save results of experimentation to a file or database
- Ideally, the ability to consume and produce files of a given format that describe an entire experiment, so that experiments could be scripted easily and shared among teams. The authors envision XML or some other descriptive format as able to suffice for this purpose.

As the feature list clearly indicates, this is a somewhat ambitious undertaking. It was decided that the creation of such a piece of software was outside the scope of this project. However, its development would likely facilitate future researcher, which would only require scripting experiments prior to implementation.

Comparison to Machine Performance

Due to technical and time constraints, experimentation in this project was confined to human subjects. However, it is the belief of the authors that similar experiments can be part of a performance baseline against which future machine vision systems can be measured. An interesting question when pondering such systems is whether context will help or hinder object recognition.

From a system design standpoint, a more complicated scene would seem, on the surface, to result in more data through which the system must sift, and thus more acrobatics for the system to perform in order to acquire and evaluate the object in question. So, for simply trained artificial vision systems, one can see where presentation of objects in context could be problematic. Conversely, simply presenting something like a chair against a plain background to such a system would allow it to more easily focus in on the subject image and identify it. However, when considering a vision system trained to consider a scene as a whole, a different view of context emerges.

Assuming such a context sensitive system keeps a catalog of all objects in a scene, using each object to reinforce its beliefs about other objects being seen, context might be of benefit. For example, if a machine was considering a living room scene and saw an end table first, it might recognize the table with a low degree of certainty. But as it recognized a sofa, a coffee table, and other items commonly found in such a room, the system's belief that it had spotted an end table would be reinforced. On the other hand, if it were presented with only an end table out of context, there would be nothing to reinforce its beliefs. The system's initial guess would therefore be its best (indeed, only) guess. In this case such a system would exhibit behavior more similar to that expected from a human subject. However, direct comparison in performance between the system and human subjects would still have to be performed with care.

When we consider the impact of context on an artificial system's performance relative to that of a human subject's it is important to remember that, in a way, such a comparison might not be fair. While the artificial system may well benefit from context when it comes to the degree of certainty with which it recognizes an object, the time in which it recognizes the object might be affected by the amount of processing it has to do. Taking again the living room example, there will certainly be a computational cost involved with recognizing each object in a scene and updating the system's beliefs about those objects. So, while a human subject might well recognize an object in a matter of a few seconds, the machine might take much longer to do so, even though it performs no worse in terms of accuracy (4).

A temporal measure of performance must, therefore, be handled carefully. If the idea is to measure efficiency of a recognition algorithm, then speed is clearly a valid yardstick against which to measure. However, recognition time should probably be considered separately from accuracy when conducting an experiment similar to the one outlined in this paper. One way of leveling the playing field for an artificial system might involve altering the speed at which images are presented to the system, perhaps delaying the next presentation until the system has finished processing the previous one (5). This would take time out of the equation, allowing recognition to be based solely on the degree to which the object under consideration is obscured by its mask (6-7).

VII. SAMPLE TESTING SHEETS AND REPRESENTATIVE SAMPLE IMAGE SET

The following pages contain samples excerpted from the instruction and data collection sheets distributed to each test subject to log responses upon recognition of each object. Included is also a representative sample of some of the images (6 of 15) used in the experiment.

Representative Sample Image Set:

Successful statistical practice, based on focused problem definition includes in sampling, defining the population from which our sample is drawn. A population can be defined as including all items with the characteristic one wish to understand. Due to lack of enough time or money to gather information from everyone or everything in a population, the goal becomes finding a representative sample (or subset) of that population.

Sample Instruction Sheet:

Please be honest and as accurate as possible with your responses.		
Image	Number on the Frame („2 to 13) ** Put 14 if you did not recognize the object until the last scene***	Name of Object
1) 4188		
2) 4190		
3) 4192		
4) 4197		
5) 4200		
6) 4205		
7) 4209		
8) 4218		
9) 4226		
10) 4237		
11) 4275		
12) 4276		
13) 4277		
14) 4279		
15) 4280		

Sample Data Sheet:

Objects in Context:

Instructions:

This slide show will contain 15 sets of scenes, with 14 images each. Please *do not* exit the slide show or press any button on the keyboard other than the "right arrow".

Your first image will contain a black box with the number 1 on it. The box will be covering an object in a scene. Please use the "right arrow" to *slowly* reveal what is behind the black box in the scene. At the moment that you *completely* recognize the object behind the black box, please *stop*, and then, in the table below, please record the **number** printed on the frame that surrounds the object. In addition, please provide in the table what you think the most appropriate **name** for that object is.

The object will become fully exposed on the 14th image. If, after you confirm the identity of the object, you happen to realize that you had originally misidentified the object, please ONLY record the frame number of the object at which *complete* recognition occurred.

Once you record the object name and frame number, honestly and as accurately as possible, please continue with the "right arrow" to the next scene. After the 15th set of scenes, the slide show will end.

Therefore, as an example, the representative sample image set is included (Fig.4.). It shows (clockwise from upper left): karaoke machine, pillow, hand towel, brown bag, bicycle tire, and model sailboat. Images were manually processed using Adobe Illustrator, Adobe Photoshop, and GIMP (GNU Image Manipulation Program)(8-9).

Figure 4: Representative Sample Image set

Apstrakt

Cilj ove studije je bio da odredi stepen informacije potrebne čoveku da dosegne kompletno prepoznavanje objekta u datom scenariju, baziranom na lokalnoj slici objekta zavisno od stepena raspoložive kontekstuakne informacije. U tu svrhu, test subjektima su predstavljene serije maskiranih objekata u kontekstu i izvan njega. Naša hipoteza je da bi kontekst snažno uticao na mogućnost test subjekata da prepoznaju objekte unutar datog scenarija. Ukupno 15 objekata iz tri posebne kolekcije slika je upotrebljeno i predstavljeno nekim subjektima u kontekstu i onim, izvan konteksta. Bazirano na ne-randomiziranoj selekciji, bilo je ukupno 10 subjekata iz dve grupe. Ukupno 5 subjekata je predstavljeno sa slikama u kontekstu. Svaka prezentacija je predstavljena testiranom subjektu dovoljno dugo da se objekt moze prepoznati. Slajd prezentacija je upotrebljena za prikazivanje objekata manualno, gde je automatski menjač slika bio onesposobljen tako da je postignuta kontrola slika od strane subjekta. Srednje vreme prikazivanja slika subjektu je bilo u intervalu 30-60 sec. Favorizujući osnovnu hipotezu, eksperimenti su pokazali da prisustvo konteksa olakšava prepoznavanje objekta. Rezultati eksperimenta su tabularno i grafički predstavljeni. Rezultati pokazuju snažnu tendenciju kontekstualnosti u pomoći brzom i tačnom prepoznanju objekta. Može se identifikovati dinamična maskirajuća sposobnost koja omogućuje aplikaciju različitih tipova maskiranja u regionu od interesa (ROI) koji sadrži objekat. Stoga se ovaj sistem može koristiti i proširiti tako da dozvoljava prepoznavanje bazirano samo na stepenu do koga je objekat posmatranja zatamnjen datom maskom. Detalji su izloženi u zaključku.

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