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13. ABSTRACT (Maximum 200 words)

The specific aim of this project is to test the hypothesis that perceptual mislocalization of a moving tactile stimulus arises from a systematic misrepresentation of stimulus location on the skin by primary somatosensory cerebral cortex (SI). Experimentally, we established that within a 1-200 cm/sec range of velocities, the path traveled by a moving tactile stimulus is represented veridically by skin mechanoreceptors (ruling out somatosensory receptors as the source of perceptual mislocalization). SI cortical experiments substantiate the original hypothesis by demonstrating that the pattern of neural activity evoked in SI cortex by a moving skin stimulus varies with stimulus velocity in a manner paralleling that of perception. In the modeling studies, a novel model of synaptic input integration by dendrites of cortical pyramidal cells was developed which enables cells to tune to higher-order stimulus features. Studies with the model also support the original hypothesis. The original computational model of SI cortical network was upgraded and incorporated the newly developed model of the cortical pyramidal cell. This network was then tested for its ability to extract higher order features of sensory input patterns as well as its application to feature extraction of objects in cluttered or noisy environments.

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Final Report

(1) Foreword

This progress report summarizes two types of work. In the first part of our study, we performed experimental analysis of the underlying cortical circuitry required to analyze objects moving across the skin. In the second part of the study, we applied the metrics that we obtained to a biologically faithful model and showed that this model was extremely efficient at detecting objects within natural cluttered scenes.

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(4) Statement of the problem studied.

The specific aim of this project was to test the hypothesis (through parallel neurophysiological experiments and neural network modeling simulations) that perceptual mislocalization of a moving tactile stimulus arises from a systematic misrepresentation of stimulus location on the skin by primary somatosensory cerebral cortex (SI). Experimentally, SI cortical experiments substantiated the original hypothesis by demonstrating that the pattern of neural activity evoked in SI cortex by a moving skin stimulus varies with stimulus velocity in a manner paralleling that of perception. In the modeling studies, a novel model of synaptic input integration by dendrites of cortical pyramidal cells was developed which enables cells to tune to higher-order stimulus features. Studies with the model also supported the original hypothesis. Additionally, this network model was tested for its ability to extract higher order features of sensory input patterns, and it was shown to be very successful at extending current techniques of nonlinear factor analysis. In this progress report, we demonstrate its use in automatic target recognition, or more specifically, in recognizing military vehicles in real-world settings.

(5) Summary of the most important results.

I. Biological findings.

An object's motion has prominent and diverse effects on its perceived position. For example, at high velocities of skin brushing stimulation, both the first and the last skin points contacted by the brush are perceived to be shifted in the direction of brush motion, and the skin path taken by the brushing stimulus is perceived to be much shorter than it really is (Whitsel et al., 1986). In vision, such effects of stimulus velocity on the perceived positions of the start and end points are known as Frohlich and Flash-Lag Effects, respectively (Whitney, 2002).

To explore the neural bases of these prominent perceptual phenomena, response of the primary somatosensory cortex (SI) to skin-brushing stimulation was studied in monkeys using the methods of near-infrared optical intrinsic signal (OIS) imaging of SI stimulus-evoked activity and extracellular recording of the spike discharge activities of SI neurons. OIS findings clearly show that the spatial distribution of the optical response in SI is velocity- and direction-dependent: (1) the region of SI activation is much smaller at 100-200cm/sec than at 10-50 cm/sec; and (2) at higher stimulus velocities the optical response shifts its location in SI in the direction of stimulus motion. In Figure 1 below, the difference in the optical responses to flutter at two locations versus a stimulus moving across the 2 points on the skin is shown. When the moving stimulus travels between two points on the skin at a relatively low velocity (5 cm/sec in this example), it activates a fairly large region of SI cortex. When the same stimulus is sped up (to 200 cm/sec), activation is observed most prominently in the cortical region that corresponds with the skin region that the stimulus is moving towards (thus, this figure demonstrates that the response of SI cortex is both velocity and direction dependent).

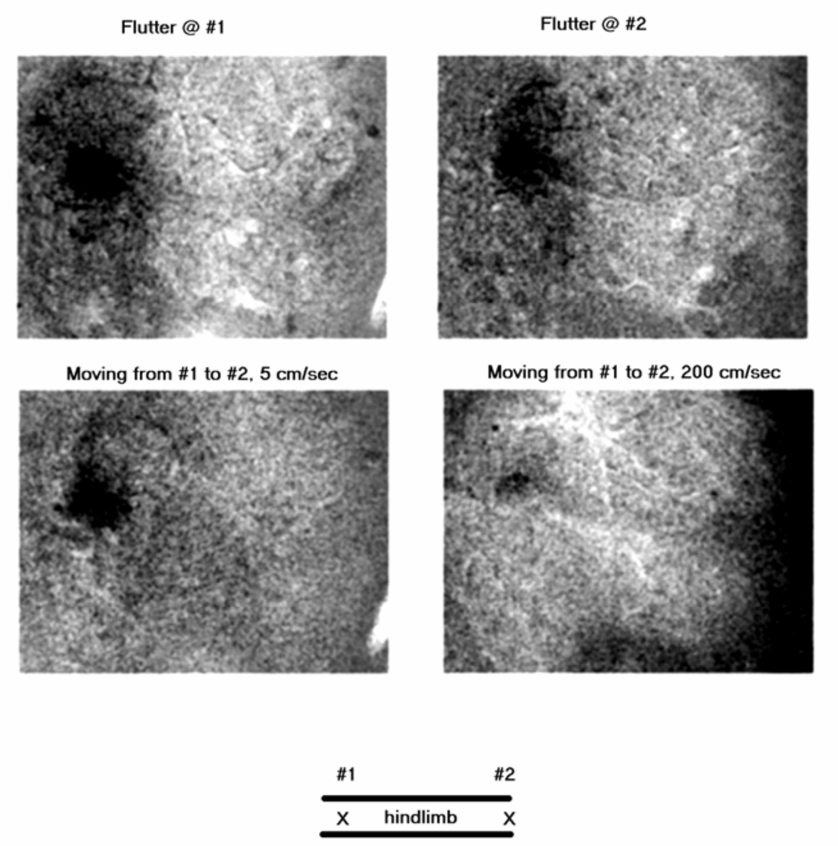

Figure 1. Imaged response of moving stimulus.

Cutaneous mechanoreceptor afferents were found to respond to low- and high-velocity skin-brushing stimulation with spike discharges that occurred at virtually the same brush positions, thus indicating that the velocity-dependent shift of OIS response in SI must have central origins. Among SI neurons, at high brushing velocities 50% of neurons in areas 3b and 1 (Group I) showed a significant displacement of stimulus-evoked firing to later positions along the stimulus path, but this shift, however, is attributable simply to the conduction delay of on average 20 msec between the skin and the SI cortex. The other 50% of neurons in areas 3b and 1 (Group II) were more interesting: although the ON-edge of their response profile also shifts with stimulus velocity due to 20 msec latency, the OFF-edge of their response profile is mostly velocity-invariant; or, more precisely, it follows a shallow U-shaped course as velocity is increased from 1 to 250cm/sec, remarkably similar to the behavior of the perceived locus of the final position of the brushing stimulus in the human tactile psychophysical studies. In another close parallel to psychophysics, the length of the response profile of Group II neurons shows the same dependency on brushing velocity, as does the perceived length of skin brushed by a stimulus. Both curves are remarkably similar in their decline at velocities from 1 to 5cm/sec, plateau between 5 and 30cm/sec, and another decline at velocities above 30cm/sec.

In conclusion, the similarity of effects of stimulus velocity on the response of Group II neurons in SI and on perceived stimulus position in human psychophysics suggests that the perceptual distortions of a brushing stimulus position on the skin have their neural counterparts in the distortions of the SI representation of the position of such a stimulus. At the same time, the existence of Group I neurons in SI suggests that these neural correlates of psychophysics are not a universal property of all SI neurons.

II. Computational Findings

As a part of this ARO-funded research project (P-43077-LS; Tommerdahl, P.I.), we have developed a computational ‘SINBAD’ model of how cerebral cortical neurons learn to recognize higher-order features in their sensory environments (Ryder and Favorov, 2001; Favorov and Ryder, 2004; Favorov et al., 2003). This work led us to formulate a novel computational ‘SINBAD’ algorithm that significantly extends current techniques of nonlinear factor analysis (Kursun and Favorov, 2004a). To demonstrate the analytical powers of this algorithm, we have successfully applied it to computer-science problems of super-resolution and human face recognition (Kursun and Favorov, 2003, 2004b). We are also currently applying a version of this algorithm (called ‘Virtual Scientist’; Kursun and Favorov, 2004a) to metabolomics, a field in functional genomics. Another challenging, but potentially valuable practical application of the SINBAD algorithm, suggested by Dr. Schmeisser, is to use it in automatic target recognition, such as, for example, recognizing military vehicles in real-world settings. This paper is a report of our initial progress on such a target-recognition task.

Approach

The study was carried out on the TNO-TM Search_2 dataset of 44 high-resolution photographs of cluttered rural scenes containing 9 types of military vehicles (Toet et al., 1998). 24 of those images were used to train our procedures. 10 other randomly chosen images were used to test their performance after training. Our approach is based on a hierarchical iterative procedure that involves: (1) learning SINBAD features characteristic of the kinds of patterns encountered in the database images and using these features to identify possible target locations, (2) developing additional SINBAD features specifically of such ‘suspicious’ locations and using these specialized features to narrow-down the set of possible target locations, (3) developing another set of even more specialized SINBAD features on this narrowed-down set of locations and using them to further reduce the number of false detections, and so on.

SINBAD features are learned by a network of SINBAD cells. Each cell implements a machine-learning algorithm designed to extract mutual information from different, but related sets of inputs (Favorov and Ryder, 2004; Kursun and Favorov, 2004a). Applying this algorithm to our target recognition problem, we use it to learn various characteristic types of local structures present in natural landscape images. Such local structures are distinguished by certain degrees of internal redundancy and this redundancy is used by SINBAD neurons both to discover such structures and to learn to distinguish among their different categories.

To make a decision on whether a given image location contains a target (a vehicle), we use a Support Vector Machine (SVM; Scholkopf and Smola, 2002). SVMs have an important advantage over other types of classifiers in that they can be successfully trained even on very limited numbers of training samples (and even when input vectors are very high-dimensional, which is our case), avoid over-fitting, have excellent generalizing abilities, and converge very quickly. The essential features of our approach are illustrated in Figure 2. The first SVM (SVM_1) is trained to respond positively when its small viewing window is placed over a military vehicle in any given training image. Of course, as can be expected, this SVM fails to learn this classification task perfectly: in order to avoid missing any vehicles, it incorrectly responds to views of nature as if they contained a vehicle on 0.35% of trials. We use SVM_1 for an initial search of a given full-size image: we scan the SVM viewing window over the entire image and select for further analysis those locations where SVM_1 responded positively. By doing this, we quickly discard 99.65% of locations in the image as of no interest. However, we are still left with a large number of locations that might contain a target.

For the second stage, we develop SINBAD features using only those image locations that were identified as ‘suspicious’ by SVM_1. For this report, we used a network of 14 SINBAD cells (‘SINBAD Network 1’ in Figure 2). Each cell learns a different feature within the same 5x5 pixel viewing window. Together, the outputs of these SINBAD cells represent the image content of a 5x5 pixel window by a vector in a 14-dimensional ‘feature’ space. SINBAD features, in turn, are used as inputs to the second SVM (SVM_2 in Figure 2). SVM_2 is trained to recognize the presence of a vehicle within a 20x20 pixel window. During training, the window is placed only at those image locations that were marked as ‘suspicious’ by SVM_1. SVM_2 greatly reduces the number of False Positives that were made by SVM_1 – currently by a factor of 20 – without missing any of the real vehicles in the test images. Thus, a sequence of SVM_1 and SINBAD-SVM_2 in our experiments so far was able to detect all the test vehicles while making False Positive mistakes on only 0.015% of the test trials.

These False Positives can be reduced further by one or more additional SINBAD-SVM stages (one such stage is shown in Figure 2). At each stage, SINBAD features can be developed specifically for those image locations that were considered suspicious by the preceding stages of the analysis. Such specialized SINBAD features will exhibit progressively greater discriminative sensitivity to image details specific to the ‘suspected’ (i.e., containing a vehicle or not yet ruled out) image locations. The enhanced sensitivity, in turn, can enable the next SVM to improve its classification performance, further reducing the numbers of False Positives.

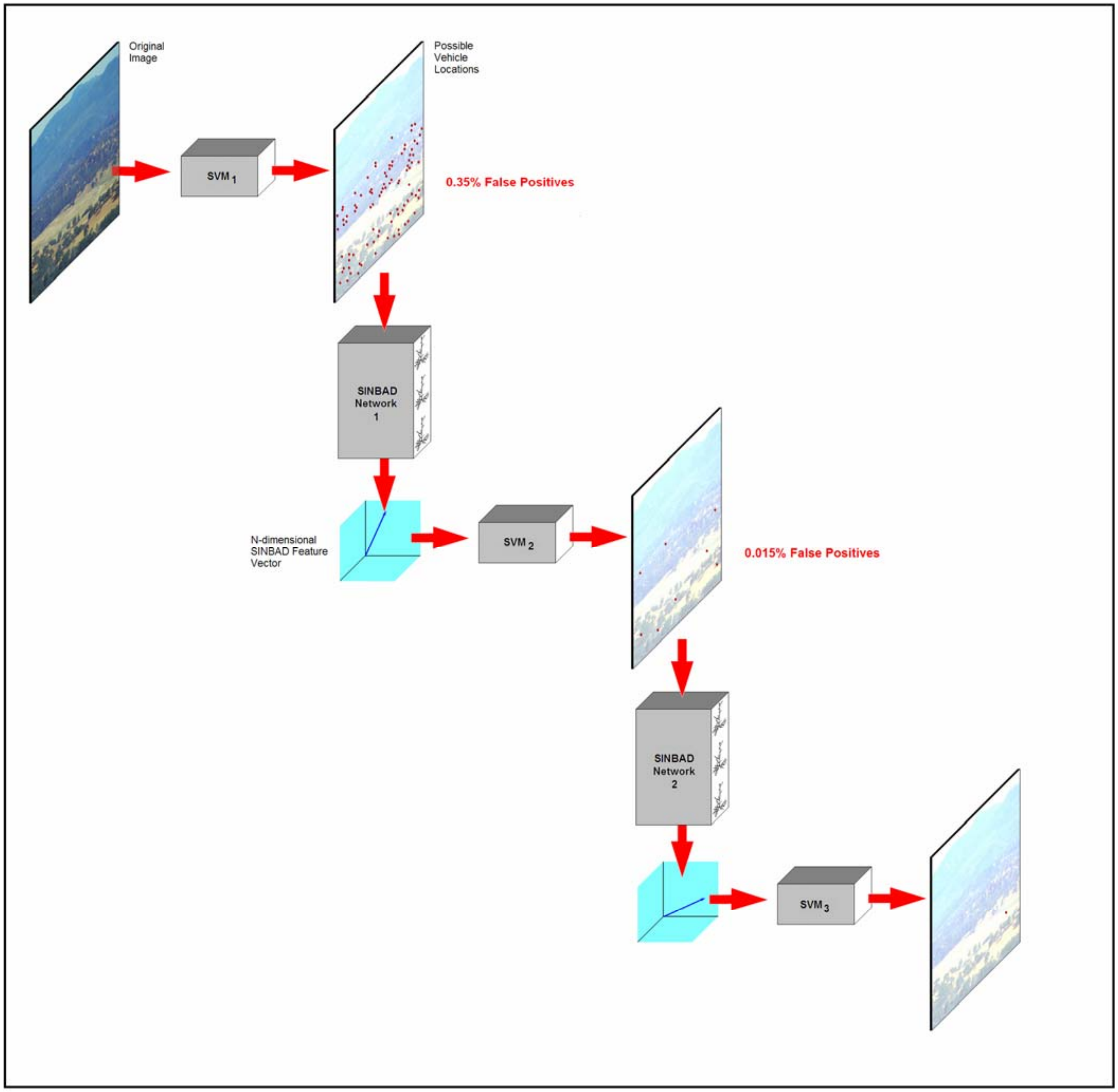
Original Image
SVM 1
Possible Vehicle Locations
0.35% False Positives
SINBAD Network 1
N-dimensional SINBAD Feature Vector
SVM 2
0.015% False Positives
SINBAD Network 2
SVM 3

FIGURE 2

Results

Figure 3 shows the outcomes of the first two stages of vehicle detection performed on one of the dataset images. This image was not used in either SVM_1 or SINBAD or SVM_2 training, but was reserved for testing the performance of those algorithms after their training. The local windows shown in the bottom two panels indicate image locations at which SVMs signaled the presence of a vehicle.

As shown in the third panel, in stage 1 SVM_1 correctly signaled the location of a tank in the image. However, it also signaled 155 other locations, which did not contain any vehicles (False Positives). In stage 2, 153 of these 155 False Positive locations were correctly discarded by SVM_2 (see the bottom panel). SVM_2 identified 8 locations in the image as possibly containing a vehicle, 6 of them correctly (covering different parts of the same tank) and only 2 incorrectly. Thus, Figure 3 demonstrates the effectiveness of our approach of developing specialized SINBAD features of suspected image locations and training a new SVM on those features in greatly reducing the numbers of False Positives without reducing the ability to find the true targets.

Figure 4 shows suspected vehicle locations identified by SINBAD-SVM_2 in six other test images. Each panel shows (1) a part of the original image, (2) suspected vehicle locations (small squares), and (3) a view in which the suspected locations and their surroundings are highlighted to make clearer the landscape structures that were mistaken by SVM_2 for a vehicle. Visual inspection of those structures shows that most of the mistaken structures do not look like vehicles (e.g., tree trunks or branches), which suggests that it should be possible for the next-stage SINBAD-SVM to learn to correctly interpret such structures as non-targets.

Interestingly, according to Toet et al. (1998) human observers had difficulties finding a vehicle in database image 11 (top-left panel in Figure 4), with 18 out of 62 observers failing to find it. Image 11 was one of our test images and, in a favorable contrast, SVM_2 had no difficulties detecting this target and, furthermore, without generating many False Positives. This superior performance was repeated on database image 2 (top-right panel in Figure 4), which was also difficult for human observers (16 out 62 failed).

In conclusion, we believe that the already impressive vehicle-detection performance achieved so far by the SVM_1-SINBAD-SVM_2 sequence can be raised even much higher by incorporating additional developments in future research studies into our set of image analysis procedures.

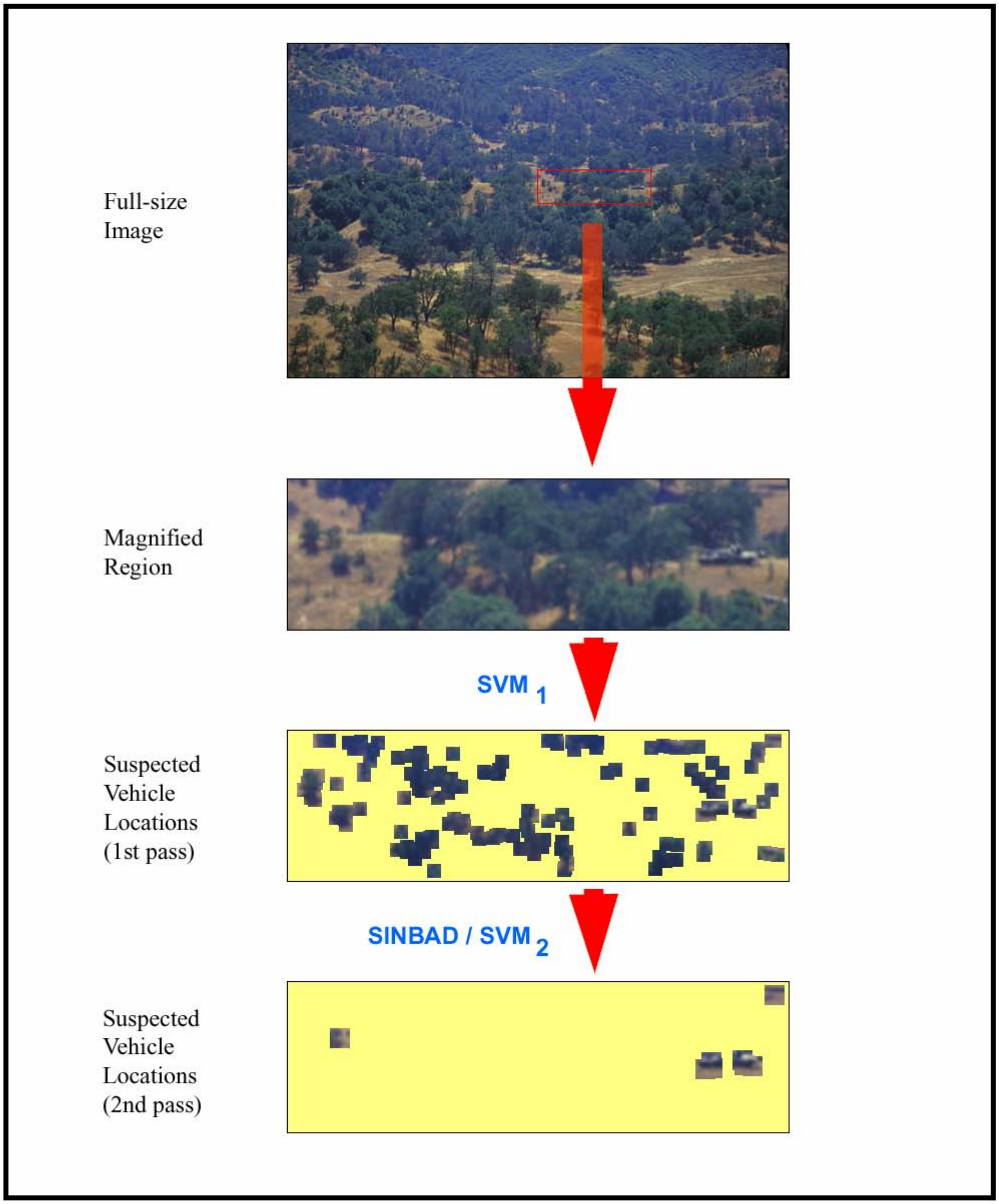
Full-size Image
Magnified Region
SVM 1
Suspected Vehicle Locations (1st pass)
SINBAD / SVM 2
Suspected Vehicle Locations (2nd pass)

FIGURE 3

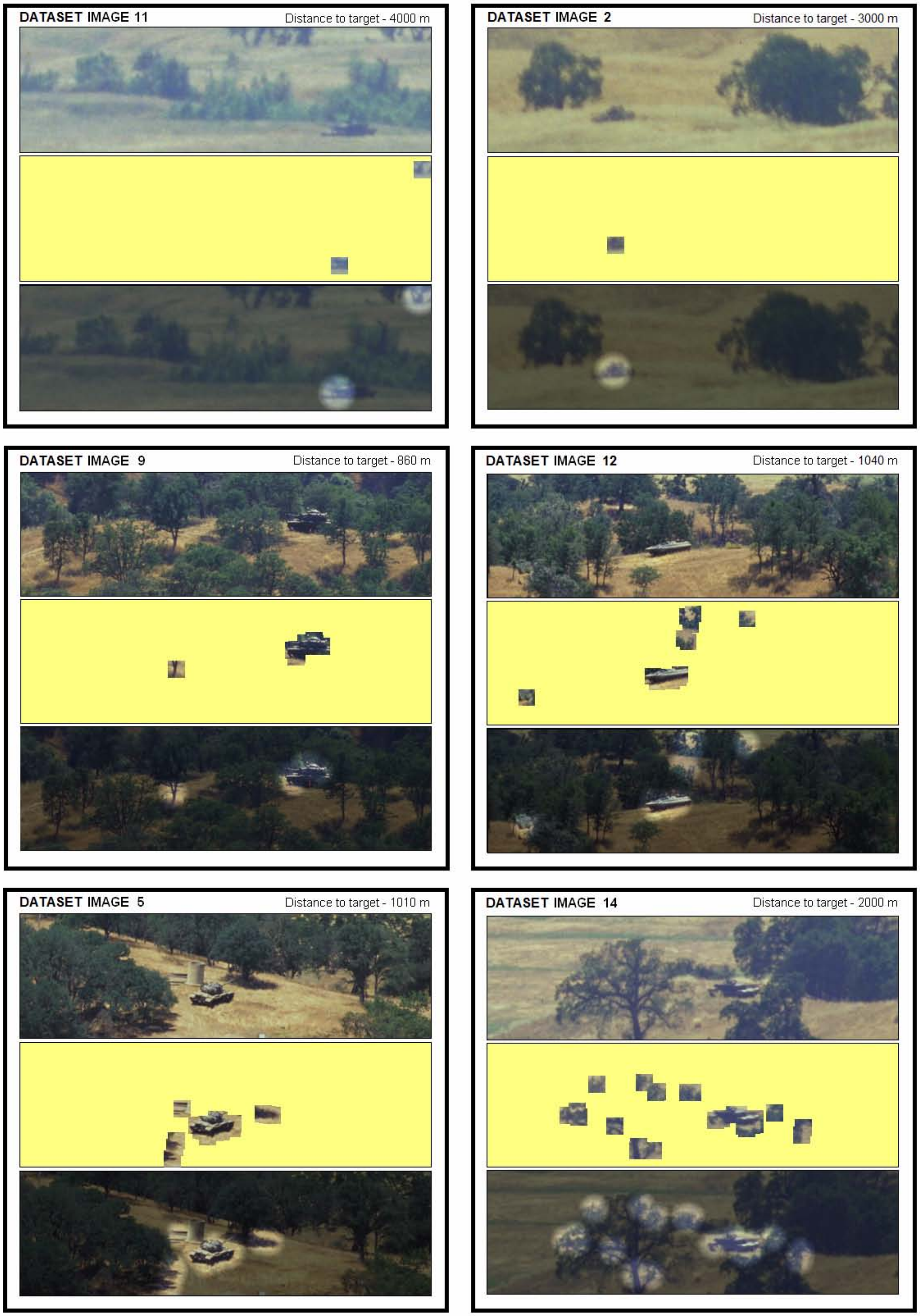
DATASET IMAGE 11
Distance to target - 4000 m
DATASET IMAGE 2
Distance to target - 3000 m
DATASET IMAGE 9
Distance to target - 860 m
DATASET IMAGE 12
Distance to target - 1040 m
DATASET IMAGE 5
Distance to target - 1010 m
DATASET IMAGE 14
Distance to target - 2000 m

FIGURE 4

(6) Listing of all Publications acknowledging this grant.

(a) Papers published in peer-reviewed journals: 10

Chiu J, Tommerdahl M, Whitsel B and Favorov O. (2005) Stimulus-dependent spatial patterns of response in SI cortex. BMC Neurosci. 2005 Jul 19;6:47, 1-14.

Favorov, O.V. and Ryder D. (2004) SINBAD: a neocortical mechanism for discovering environmental variables and regularities hidden in sensory input. *Biological Cybernetics* 90: 191-202.

Favorov, O. V., Ryder, D., Hester, J. T., Kelly, D. G. and Tommerdahl, M. (2003) The cortical pyramidal cell as a set of interacting error backpropagating networks: a mechanisms for discovering nature's order. In : *Theories of the Cerebral Cortex*, R. Hecht-Nielsen and T. McKenna (eds.), Springer, London, pp.25-64.

Kursun O, Tommerdahl M, Reynolds M and Favorov O. (2005)Robust unsupervised facial feature extraction and use in matching images of never-before-seen individuals in homeland security applications. Artificial Neural Networks in Engineering,. (ANNIE 2005)

Kursun O. and Favorov O.V. (2003) Single-frame super-resolution by inference from learned features. *Istanbul University Journal of Electrical and Electronics Engineering* 3: 673-681.

Kursun, O., and Favorov, O. V. (2004). SINBAD automation of scientific discovery: from factor analysis to theory synthesis. *Natural Computing* 3: 207-233.

Kursun O. and Favorov O.V. (2004) What can SVMs teach each other? *Artificial Neural Networks in Engineering* (ANNIE 2004).

Simons S, Tannan V, Chiu J, Favorov O, Whitsel B, and Tommerdahl M. (2005) Amplitude-Dependent Response of SI Cortex to Vibrotactile Stimulation. BMC Neuroscience, Jun 21; 6:43, 1-13.

Tommerdahl M., Favorov OV and Whitsel BL. (2005) Effects of high-frequency skin stimulation on SI cortex: Mechanisms and functional implications. Somatosensory and Motor Research, 22 (3).

Tommerdahl M, Simons SB, Chiu J, Favorov OV, Whitsel BL. (2006) Ipsilateral input modifies the SI response to contralateral skin flutter. J Neurosci,. 2006 May 31;26(22):5970-7

(b) Papers published in non-peer-reviewed journals or in conference proceedings: 8

Joshi, S., O. Kursun and O. Favorov. Exploiting the Structure of Order: An application to natural images. The 7th World Multiconference on Systemic, Cybernetics, and Informatices (SCI 2003), Orlando, Fl, July 27-30, 2003

Kursun, O., Favorov, O.V. (2004) SINBAD: towards an implementation-independent hidden-variable discoverer. 2nd International Conference on Computing, Communications and Control Technologies (CCCT), Austin, TX

Kursun, O. and O. Favorov. Unsupervised order extraction and use in natural images. The 12th International Conference on Image Analysis and Processing, Mantova, Italy. September 17-19, 2003

Kursun, O. and O. Favorov. Automated theory building by Virtual Scientist. Workshop on the Future of Neural Networks (FUNN 2003) at Thirtieth International Colloquium on Automata, Languages and Programming (ICALP 2003), Eindhoven, The Netherlands, June 30-July 4, 2003

Kursun, O. and Favorov, O. (2003) Finding Hidden Representations by Sinbad Network. Twelfth International Turkish Symposium on Artificial Intelligence and Neural Networks (TAINN) Istanbul, Turkey, July 2-4, 2003.

Kursun, O., Joshi, S., and Favorov, O.V. (2002) Single-frame super-resolution by inference from learned features. 11th Turkish Symposium on Artificial Intelligence and Neural Networks (TAINN), Istanbul, Turkey.

Kursun, O., Joshi, S., and Favorov, O.V. (2002) Super-resolution by unsupervised learning of high level features in natural images. 6th World Multiconference on Systemics, Cybernetics and Informatics (SCI), Orlando, USA.

Tommerdahl M., Chiu J, Whitsel BL., and Favorov O. (2005) Minicolumnar patterns in the global cortical response to sensory stimulation. In: Neocortical Modularity and the Cell Minicolumn, Manuel F. Casanova, M.D., ed., NOVA.

(c) Papers presented at meetings, but not published in conference proceedings

None

(d) Manuscripts submitted, but not published

Simons SB, Chiu JC, Favorov OV, Whitsel BL, Tommerdahl M. (2006) Duration-dependent response of SI cortex to flutter stimulation. *In Revision*.

(e) Technical reports submitted to ARO

None

(7) List of all participating scientific personnel showing any advanced degrees earned by them while employed on the project

none

(*8) Report of Inventions (by title only)*

none

(9) Bibliography

Favorov, O.V. and Ryder D. (2004) SINBAD: a neocortical mechanism for discovering environmental variables and regularities hidden in sensory input. *Biological Cybernetics* 90: 191-202.

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Whitney (2002) The influence of visual motion on perceived position. *TRENDS in Cognitive Sciences* 6: 211-216.

Whitsel et al. (1986) Dependence of the subjective traverse length on velocity of moving tactile stimulus. *Somatosensory and Motor Research* 3: 185-196.

(10) Appendices - none